LOCAL ECOLOGICAL FOOTPRINT USING PRINCIPAL COMPONENT ANALYSIS: A CASE STUDY OF LOCALITIES IN ANDALUSIA (SPAIN)**

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ABSTRACT

The quantity and quality of available information is one of the major constraints for the calculation of the ecological footprint, particularly for sub-national or sub-regional territorial levels. At the national or even regional level, the information that allows for computing the ecological footprint is generally available. However, when trying to calculate the footprint for lower-level territorial realities (e.g., cities or municipalities), this information is insufficient or non-existent. In this article, we propose an indirect method for calculating the ecological footprint of such territorial spaces through Principal Component Analysis. The case study utilises the ecological footprint of Andalusia (a Spanish region) as a starting point for footprint assignment to each of the 771 municipalities included in the Andalusian region. A set of variables related to the consumption levels in these municipalities has been utilised and is expressed in physical units. These variables make it possible to obtain a weighting factor to determine the ecological footprint of each municipality. This procedure also makes it possible to identify which variables or indicators have the greatest impact on the ecological footprint for a given territory. According to the results, the method also shows how inappropriate it is to consider the population as a way to distribute the ecological footprint; there are relevant differences between the weight of the population in municipalities and their generated footprint. There are also significant differences between the magnitude of economic indicators, such as GDP, and the estimated ecological footprint; for municipalities with higher income levels, the ecological impact is more than proportional to the weight of the monetary indicators.

KEY WORDS: Ecological Footprint; Principal Component Analysis; Territorial Disparities

JEL CLASSIFICATION: B40; C38; R12

HIGHLIGHTS

- In the absence of sufficient data, Principal Component Analysis can be used to estimate the local EF.
- Ecological Footprint of 771 localities of Andalusia was estimated.
- This method makes possible to identify the indicators with the greatest impact.
- Territorial disparities in physical terms are even greater than in the monetary terms.

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1. INTRODUCTION

In the context of the ecological footprint (hereafter EF), this article focuses on methodological aspects of its computation and applicability to a smaller scale than the national or regional level. The primary goal of this work is to provide a method to estimate the ecological footprint (EF) of territories where the standard methodology cannot be applied due to insufficient information. From an initial EF computed for a larger territory, we distribute this value among the smaller territories according to the resource consumption levels described through a set of variables or indicators.

This objective is essential and highly relevant because there are numerous places of high economic, social and environmental importance (e.g., urban areas and metropolitan areas) for which there is insufficient information for the direct calculation of the ecological footprint.

The following points describe complementary objectives of this work: (1) to further analyse the territorial disparity within the spatial units for which EF is calculated; (2) to identify the variables or indicators in each territory with the greatest impact on the EF; (3) to compare EF evolution with other indicators (e.g., GDP, occupied surface, population); and (4) to correlate the productive specialisation of a territory with the intensity of resource consumption expressed through the EF.

Various studies have tried to mitigate the limitations caused by the lack of information for the EF calculation, specifically for local and urban contexts. To provide an account of the *state-of-the-art* for such research, a number of the most relevant studies in this regard are discussed. The majority of the approximations applied to the estimation of the ecological footprint for local areas have been based on estimates of the state footprint that are weighted by the local population distribution (Folke *et al.*, 1997; Wackernagel, 1998). As the authors have acknowledged, the main limitation of this procedure is the assumption of a homogeneous behaviour of the population across all the areas considered, when the calculation of the EF is really intended to discriminate or distinguish among the behaviours of populations in relation to resource consumption.

Other studies (Barrett, Scott and Lindfield, 2001; Pacholsky, 2003; Muñiz and Galindo, 2005; Jin *et al*., 2009; Li *et al*., 2010) utilised the component-based model[1] introduced by Chambers, Simmons and Wackernagel (2000) as a different procedure to compute the EF, without renouncing the usage of the standard methodology. Such a procedure –according to their authors– has certain advantages compared with the standard approach (compound approach), it is easier to communicate and is more instructive. However, the "disadvantages can mainly be traced to problems with data variability and reliability, which make national and international comparisons problematic. Calculating the direct and indirect life cycle impacts is highly data-intensive – quite small changes in assumptions and data sources can lead to differing results. The need to carefully consider the life cycle effects of each component in detail is a definite barrier to widespread adoption of this method" (Chambers, Simmons and Wackernagel, 2000:69).

[1] "In the component-based model the ecological footprint values for certain activities are pre-calculated using data appropriate to the region under consideration. For example, to calculate the impact of car travel data on fuel consumption, manufacturing and maintenance energy, land take and distance travelled are sourced for the region in question –then an average ecological footprint estimate is derived for a single passenger-km or other appropriate unit… The aim is to account for the most consumption with a series of component analyses…" (Chambers, Simmons and Wackernagel, 2000:68-69)

The method proposed here attempts to alleviate the above-mentioned limitations. On the one hand, the calculation of the ecological footprint for a territory of a larger size is based on a standard methodology. This approach ensures comparability. On the other hand, the variables included in the proposed method characterize the variations in the consumption patterns of the smaller scale local areas for which the EF is estimated. Thus, in this approach, the intensity of consumption is the weighting factor, instead of the population size.

The article is organised into five sections, including the introduction. The second section briefly reviews some methodological contributions and previous EF analysis studies; in particular, studies that refer to the local and urban scope and that are centred on specific contributions oriented to counteract the lack of information. The third section proposes a new EF computational methodology, the main point of this article. The fourth section discusses the main results of this paper. Finally, the fifth section summarises the most relevant aspects and presents the main conclusions.

2. METHODOLOGY

The research presented in this paper utilises Principal Component Analysis to estimate the scale of human activity in municipalities of Andalusia (see Appendix A).

The proposal is based on the EF computation for the whole Andalusian region. For this value, the authors have utilised the standard methodology (Wackernagel and Rees, 1998; Chambers, Simmons, and Wackernagel, M., 2000; Network, G. F., 2011). This approach has been possible because the necessary information was available except for the trade balance in physical terms, which is necessary to determine apparent consumption. Regarding apparent consumption, the imports and exports in physical terms have been estimated based on monetary ratios provided by the Input-Output Tables of Andalusia. The computation of the Andalusian EF is not further developed here. Instead, what has been performed is an actualisation for the 2010 period of previously realised estimates described in previously published papers (Cano-Orellana, 2004; 2007; 2009).

Based on the regional EF, we try to spatially distribute this value among the 771 municipalities in the region (main objective or primary goal). Principal Component Analysis allows this distribution. The weighting factors (scores associated to each municipality of each component, Z_{hi}, in the Appendix A) will be used to locally assign the EF. In our case, only one main component has been defined to explain most of the variance of the utilised variables (indicators of the consumption level).

The weighting factors account for the information in a set of consumption indicators (variables) quantified for each municipality. To the extent that these indicators best represent the consumption intensity in each spatial unit considered, the more reliable the EF assignment will be.

To select the consumption intensity indicators, a linear regression model has been applied, in which the indicators correspond to the independent variables. As a variable to be explained, any aggregate that reflects the total consumption in the considered spatial units could be used as a proxy variable. This method allows, in turn, as explained below, the identification of the degree of influence of these indicators or variables on the intensity of consumption for each spatial unit. Consequently, the value taken by the EF in each of the spatial units being considered can be computed.

For the case study in this paper, six variables or indicators of consumption have been used for each spatial unit (771 Andalusian municipalities): electricity consumption, urban solid wastes, vehicle stock, establishments, housing stock, and restaurants and hotels (bed-spaces). The expressiveness and representativeness of these variables has been proved adequate. The regression model has a determination coefficient of 0.9893 for a proxy variable corresponding to the municipality income (see Appendix B). The data have been obtained from the Institute of Cartography and Statistics of Andalusia.

This method also allows for a detailed analysis of the influence of indicators or variables on the weight of each municipality (see Appendix A, the "u" coefficients in equation (1)). As a consequence, it is possible to collect information regarding the effect of these indicators or variables on the EF of each municipality. This information might be relevant to guiding better management and sustainability planning.

4. CASE STUDY. MAIN RESULTS AND DISCUSSION

The proposed methodology has been applied to a Spanish region, Andalusia, located in the south of the Iberian Peninsula (Lat: 38º44' N, 36º00' N; Long: 1º38'W, 7º31'W). It has a total area of 87,589.9 square kilometres (17.3% of the national Spanish territory) and a population that corresponds to 17.9% of the Spanish population, as of 2011. The EF computation has been performed following the standard method, given that there is available data for this region. Once the EF was computed for the 2010 period, we applied the methodology described in section 3 to estimate the EF for each of its 771 municipalities (main objective or primary goal).

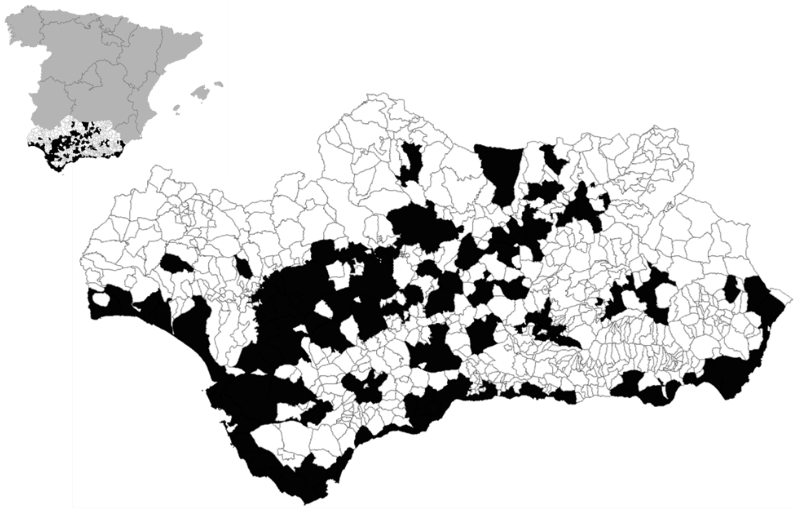
The results obtained validate the proposed method in two ways. First, from a statistical point of view, the results are robust (see Appendix A). In second place, the method can be applied to similar cases of territorial units with existing standard EF calculations and composed of spatial units of smaller scale for which the standard EF cannot be computed.

Regarding the complementary objectives, given the methodological nature of this article, we briefly describe several of the most relevant aspects of the application of the method for illustrative purposes.

Figure 1 shows the municipalities that exceed the average EF in Andalusia and the municipalities with EF values below the average. Clearly, the EF in Andalusia is unevenly distributed within the territory. The map reveals a dual economic and demographic model (complementary objective 1). The majority of the Andalusian territory (639 municipalities corresponding to 69.0% of the Andalusian surface) has an EF below the average value. In 2011, these municipalities included 23.3% of the total Andalusian population, corresponding to 16.5% of the total income, with an EF that represented 3.9% of the total EF. These municipalities have experienced long periods of rural population loss, with a weak and poorly diversified economic base. To a great extent, these municipalities have been apart from the growth and capitalisation processes, even though they include a significant part of the natural heritage of Andalusia. These rural areas perform basic regulatory functions and provide supply services and natural resources towards maintaining and reproducing the growth model in the areas most valued by the capital (Delgado-Cabeza, 2002; 2006).

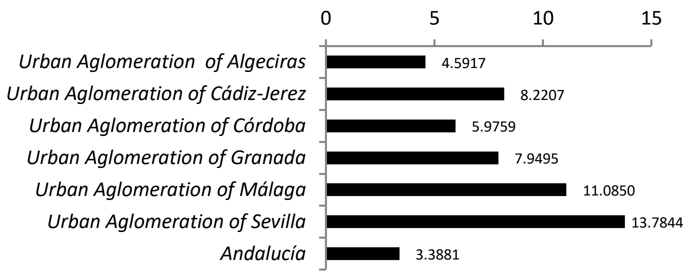
This part of the Andalusian territory is largely serving the growth and accumulation needs of the most dynamic part of the regional territory, consisting of 132 municipalities with an EF above the regional average. In 2011, the municipalities above the regional average corresponded to 31.0% of the total surface, 76.7% of the population (72% in 1981), 83.5% of the total income, and 96.1% of the Andalusian EF (complementary objective 3). Basically, this part of the Andalusian territory includes the great urban agglomerations, located around the province capitals and the Andalusian coast; this last area has economic and demographic dynamics centred on tourism and/or intensive agriculture (Cano-Orellana, 2009, Delgado-Cabeza, 2014, Delgado *et al.*, 2014).

Fig. 1
Ecological footprint of the municipalities of Andalusia. Municipalities in which the EF exceeds the mean for Andalusia are coloured black.



The 6 great urban agglomerations in Andalusia (Fig. 2) are defined in the Plan de Ordenación del Territorio de Andalucía (Consejería de Obras Públicas y Transporte, 2006). These urban zones occupy 9.5% of the regional surface, include 45% of the total population, account for 55% of Andalusian income, and represent 79.6% of the total EF of the region. According to the obtained estimates, these urban agglomerations include 84 municipalities that need 38.8 times the surface they occupy to cover their consumption levels.

Fig. 2
Ecological footprint of the Andalusian urban agglomerations. (hga/pc)



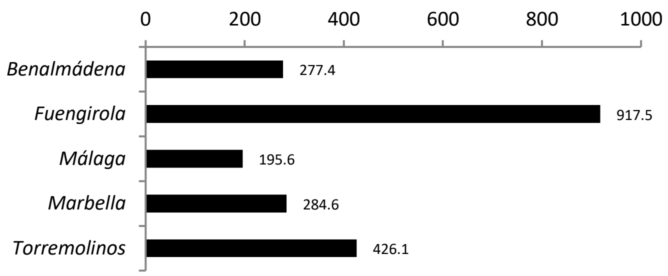
Within these 6 urban agglomerations, the weights of the provincial capitals (Cádiz, Córdoba, Granada, Málaga y Sevilla) stand out. These weights correspond to 71.7% of the total Andalusian EF.

The Andalusian coast is 859 km long. It is under significant pressure because Spain, Andalusia in particular, is one main tourist destination worldwide. In 2010, the Andalusian municipalities, especially along the coast, received 7.4 million tourists from international origins. The tourists that visited Andalusia accounted for 26.5 million people (Instituto de Estudios Turísticos –IET, 2011), more than three times its population (8.4 million for inhabitants). Tourism, despite the international economic crisis, has sustained positive growth rates. In fact, according to the latest published data from 2013, tourism in Andalusia grew 4% with respect to the previous year, increasing its participation in the regional GDP, reaching 12.9% of the overall Andalusian GDP (Consejería de Turismo, Comercio y Deporte, 2013).

The increase in anthropogenic pressure and the corresponding damage represents a serious threat for the present and future sustainability of the littoral. In fact, according to the Millennium Ecosystem Assessment (MA) by the United Nations (2005), the ecosystem in the Spanish littoral was presenting one of the most negative situations, especially because of its increasing urbanisation (UNWTO; UNWTO, 2011). From 1985 to 2012, an average of 8 hectares has been paved every day along the Spanish coast, in which Andalusia is included (Greenpeace, 2013). From 1985 to 2009 and within a 500 m wide border, the population on the Andalusian coast has increased by 35.5%, and paved surfaces within Andalusia has increased by 54.9% (Consejería de Agricultura, Pesca y Medio Ambiente, 2013).

The 62 municipalities in the Andalusian littoral occupy 9.5% of the Andalusian surface. They represent 35.6% of the population, 36.0% of the generated income, and 44.9% of the EF of the region. A total of 77.1% of this EF corresponds to locations in Costa del Sol, including the capital, the city of Málaga. That is, 14 municipalities that occupy 1.6% of the total Andalusian surface account for 14.5% of the population and 14.8% of the income. These municipalities are responsible for nearly 35% of the total ecological footprint generated in Andalusia. The significant difference between the weight of the population and the ecological footprint is related to the resource consumption associated with tourism activity, a productive specialisation with a strong environmental impact that is captured by the computed EF. Figure 3 shows the ecological deficit of the main locations in Costa del Sol, expressed in terms of the difference between the area required to satisfy their resource consumption level and their administrative surface. In some cases, such as the town of Fuengirola, there is an ecological deficit 917.5 times its area (complementary objective 4).

Fig. 3
Required surface in relation with the existing surface.



As can be observed, the results show that the municipalities in the littoral and the great urban agglomerations account for most of the total Andalusian EF. In particular, 135 municipalities corresponding to 17.3% of Andalusia's surface include 65.1% of the population, 72.8% of the income, and 94.7% of the EF of the Andalusian region.

These results reveal that in the areas where the greatest economic activity is located, the ecological costs concentrate in greater proportion than the monetary values associated with this activity. A certain degree of inefficiency in resource usage stands out in relation to the concentration of activities, in contrast to the potential gains in efficiency valued in monetary terms typically conferred on agglomeration-based economies (Krugman, 1991; 1997) according to conventional economic thinking (Galbraith, 1958; Kapp, 1970).

The results show the different intensities of resource consumption within the various considered areas. This information offers a considerable advantage over the frequently used criterion based on assigning the total ecological footprint to territorial units of lesser scale and using the population as a weighting value. Using the population as a weighting factor implies the assumption of homogeneous behaviour in its resource consumption and waste generation for the different territories, with no discrimination of the behaviours associated with institutional, economic, social, and cultural factors.

Moreover, the procedure proposed in this paper makes it possible to observe, in each municipality, the relative importance of each indicator or variable utilised as a proxy variable of the consumption intensity and, as a consequence, also makes it possible to identify the main drivers of the environmental impact in each municipality (complementary objective 2).

Table 1

Relative importance of each indicator

	1	2	3	4	5	6	Total
Fuengirola	22.0	7.3	11.9	10.0	35.1	13.6	100,0
Torremolinos	13.1	7.6	8.8	9.0	48.4	13.1	100,0
Los Barrios	4.6	75.2	4.1	5.5	6.7	4.0	100,0
San Roque	1.5	71.9	4.8	6.0	9.8	6.1	100,0

1 Urban Solid Wastes; 2 Electricity Consumption; 3 Establishments; 4 Vehicles; 5 Restaurants and Hotels (bed-spaces); 6 Housing

Table 1 presents an example with data regarding four municipalities. In the first two municipalities, Fuengirola and Torremolinos, which are important tourism centres, the most significant indicator is "Restaurants and Hotels (bed-spaces)". In the next two municipalities, San Roque and Los Barrios, where there is an important industrial chemical complex, the most relevant variable (indicator) is “Electricity Consumption”, greater than 70% in both cases.

As the number of variables or indicators increases, the chances to discriminate the main drivers of the environmental impact with greater precision also increase.

5. CONCLUSIONS

The proposed methodology in this work has allowed satisfactory achievement of the pursued objectives. The statistical consistency of the results confirms this fact. This methodology can be applied in all cases that are analogous to the studied case. The EF, computed through the standard procedure for a specific territorial unit made up by smaller units, makes it possible to assign an EF to each unit. The proposed weighting factor, based on Principal Component Analysis, allows for the observation of the consumption intensity in each of the sub-units through a set of indicators or variables expressed in physical units.

This work has also validated the proposed methodology regarding the identification of the variables for each territory with the greatest impact on the EF. This identification of the elements contributing most to the territorial EF will ease the diagnosis as well as the design and implementation of public policies towards sustainability planning and management.

This paper highlights the inadequacy of using the population as a method to distribute the EF. In our case study, there are significant differences between the population weight in different municipalities and their generated EF. There are also important differences between economic indicators, such as the GDP, and the estimated EF. In the municipalities with the greatest income levels, the ecological impact is more than proportional to the relative weight of the monetary indicators (e.g., GDP). This result implies the appearance of strong "un-economies" when the ecological dimension is considered in the territorial analysis for the wealthier areas. These results cast doubt on the supposed advantages that, under the standard economic focus, are associated with the spatial agglomeration of economic activities.

The results have made it possible to relate the productive specialisation of the considered spaces to the consumption intensity of resources. In our case, we have placed special emphasis on tourism, mainly located along the littoral, and its relation to the magnitude of the generated EF.

Appendix A. Methodology.

PRINCIPAL COMPONENT METHOD

Thus we have a *p* set of variables, X_1, X_2, …, X_p, typed or expressed in deviations from the mean.

The first principal component, like the rest, is expressed as a linear combination of the original variables:

$$Z_{1i} = u_{11}X_{1i} + u_{12}X_{2i} + \ldots + u_{1p}X_{pi}$$

For the set of the *n* observations (municipalities, in this case):

$$\begin{pmatrix} Z_{11} \\ Z_{12} \\ \ldots \\ Z_{1n} \end{pmatrix} = \begin{pmatrix} X_{11} & X_{21} & \ldots & X_{p1} \\ X_{12} & X_{22} & \ldots & X_{p2} \\ \ldots & \ldots & \ldots & \ldots \\ X_{1n} & X_{2n} & & X_{pn} \end{pmatrix} \begin{pmatrix} u_{11} \\ u_{12} \\ \ldots \\ u_{1p} \end{pmatrix}$$

This first component is obtained to maximise its variance and so guaranteed that it will be the component which will include the maximum amount of information contained in the original variables.

The variance of this first component (given that its mean is zero) is given by

$$Var(Z_1) = \sum Z_{1i}/n = (1/n)Z_1'Z_1 = (1/n)\, u_1'X'X\, u_1 = u_1' \left[(1/n)X'X\right] u_1$$

If the variables are expressed in deviations from the mean, (1/n) X´X, is the covariance matrix that we call V; if they are typed (1/n) X´X is the correlation matrix, (R).

It can be verified that u_i is the eigenvector associated with the maximum eigenvalue of the matrix V.

The variance of the *h*th component will be:

$$Var\,(Z_h) = u_h'V\,u_h = \lambda_h$$

So, the proportion of the total variance included in the *h*th principal component is given by $\lambda_h/\sum\lambda_h = \lambda_h$/trace V. In the case of typed variables, V=R, the proportion of variance associated with *h*th component is λ_h/p.

Having calculated the coefficients, u_{hj}, (component of the normalized eigenvector associated with the *h*th eigenvalue of the matrix (1/n) X´X for the principal component Z_h) we can obtain the scores, weights in this case, associated with each municipality for each principal component, Z_{hi}, from the following equation:

$$(1) \qquad Z_{hi} = u_{h1}\,X_{1i} + u_{h2}\,X_{2i} + \ldots\ldots + u_{hp}\,X_{pi}; \quad h=1, \ldots p; \quad i=1, \ldots n$$

If the first principal component explains a part of the total variance satisfactorily, the scores for that component, Z_{hi}, i=1, 2, …, n, are used as weights of the total footprint to be distributed among minor territorial entities. As the mean of Z_{hi}, i=1, 2, …, n, is zero, we can use a change of scale to turn these coefficients into weights.

If the part of the total variance explained by the first component is insufficient, other components should be used until these cover a satisfactory proportion of the total variance. Weights for the local footprint will be constructed as a linear combination of the coefficients of the components used and weighed, as well as in relation to the part of variance explained by each component.

PRINCIPAL COMPONENT ANALYSIS. AN APPLICATION TO THIS PURPOSE[2]

To examine the suitability of these data for factor analysis, Kaiser–Meyer–Olkin (K-M-O) and Bartlett tests were executed. K-M-O is a measure of sampling adequacy that indicates the proportion of variance, which is common variance. High value (close to 1) generally indicates that factor analysis may be useful. If K-M-O test value is close to 0.90 it is excellent, if it is close to 0.80 it is good, if it is close to 0.70 it is tolerable, if it is close to 0.60 it is mediocre, and if it is lower than 0.50 factor analysis it will not be useful. Bartlett's test of sphericity indicates whether the correlation matrix is an identity matrix, which would indicate that the variables are unrelated. A significance level of 0 indicates that there are significance relationships between variables. Finally, PCA was applied to normalised data, so that the covariance matrix coincides with the correlation matrix.

Table A1
Descriptive Statistics

Original variables	Mean	Std. Deviation	Analysis N
USW	5059.06	19,599.415	772
EC	45,253.68	170,501.025	772
ES	708.32	3,105.812	772
VS	7,717.01	27,524.377	772
RP-HP	1,387.98	5,172.043	772
HS	5,646.10	19,304.851	772

USW: Urban Solid Wastes; EC: Electricity Consumption; ES: Establishment Stock; VS: Vehicle Stock; RP-HP: Restaurant and Hotel (bed-spaces); HS: Housing Stock.

The figure 772 refers to 771 localities plus Andalusia as a mean.

Table A1 shows the descriptive statistics (mean, standard deviation) and the number of observations. The univariate option was used in SPSS. In fact, the only way to see how many cases were actually used in the PCA is to include the univariate option.

Table A2
Correlation Matrix

Original variables		USW	EC	ES	VS	RP-HP	HS
Correlation	*USW*	1.000	0.858	0.952	0.960	0.829	0.959
	EC	0.858	1.000	0.901	0.904	0.708	0.900
	ES	0.952	0.901	1.000	0.992	0.779	0.989
	VS	0.960	0.904	0.992	1.000	0.762	0.993
	RP-HP	0.829	0.708	0.779	0.762	1.000	0.809
	HS	0.959	0.900	0.989	0.993	0.809	1.000
Sig. (unilateral)	*USW*		0.000	0.000	0.000	0.000	0.000
	EC	0.000		0.000	0.000	0.000	0.000
	ES	0.000	0.000		0.000	0.000	0.000
	VS	0.000	0.000	0.000		0.000	0.000
	RP-HP	0.000	0.000	0.000	0.000		0.000
	HS	0.000	0.000	0.000	0.000	0.000	
Determinant = 3.909E-7							

Table 2 provides the correlations between the original variables. Before carrying out PCA we want to verify the correlations between the variables. In this study, as we can

[2] The statistical analysis has been carried out using SPSS v.22 software.

observe, the correlations are above 0.70 in all cases; the determinant of the matrix is close to 0, as are the significance levels. The results therefore indicate that there are significance relationships between the variables.

Table A3
K-M-O and Bartlett tests

Kaiser-Meyer-Olkin measure of sampling		0.811
Bartlett's test of sphericity	Approx. Chi-square	11,334.115
	Dg	15
	Sig.	0.000

Table A3 shows the results obtained by K-M-O measure and Bartlett's test of sphericity. In this study the K-M-O measure is 0.811 (more than 0.80). The significance in the Bartlett test is close to 0, so the null hypothesis is rejected and the test is significant.

Table A4
Communalities

Original variables	Initial	Extraction
USW	1.000	0.949
EC	1.000	0.853
ES	1.000	0.970
VS	1.000	0.970
RP-HP	1.000	0.723
HS	1.000	0.982
Extraction Method: Principal Component Analysis		

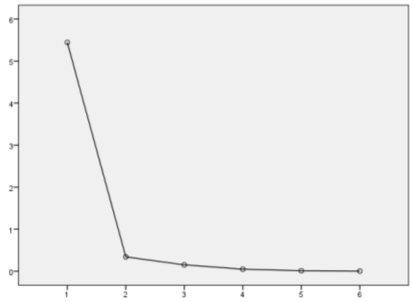
Table A4 indicates that the initial value of the communalities in PCA is 1 (1st column). The extraction column indicates the proportion of variance of each variable that can be explained by the principal component. We can see that all variables show high values, and as a result, are well represented in the common factor space.

Table A5
Total Variance Explained

	Initial eigenvalues			Extraction sums of squared loading		
Component	Total	% of variance	% cumulative	Total	% variance	% cumulative
1	5.446	90.764	90.764	5.446	90.764	90.764
2	0.342	5.692	96.456			
3	0.151	2.511	98.968			
4	0.049	0.812	99.780			
5	0.010	0.175	99.954			
6	0.003	0.046	100.000			
Extraction Method: Principal Component Analysis						

Table A5 shows the components extracted during PCA, so many components have been included as variables. This table shows how much of the total variance of the original variables is explained by each of the principal components. As PCA is conducted on the correlation matrix, the variables are standardised, which means that each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis (in this case, 6). In the present study, the first component (scaled eigenvector) explains the largest part of the total variance, and has a variance (eigenvalue) of 5.4, amounting to 90.8 per cent of the total variance. In consequence, the number of factors considered is only one, which will be used to transfer the ecological footprint of Andalusia to its 771 localities one by one.

Fig. A1
Scree Plot



The Scree Plot (Fig. A1) graphically represents the distribution of variance among the components. For each principal component, the corresponding eigenvalue is plotted on the y-axis. If the curve shows an “elbow” at a given value on the x-axis, this is taken to indicate that higher order principal components contribute a decreasing amount of additional variance and therefore might not be needed. We can see these values in table 5, where the second component on the line is practically parallel to the x-axis. This means that each successive component accounts for decreasing amounts of the total variance.

Table A6
Component Matrix[a]

	Component
	1
USW	0.991
EC	0.985
ES	0.985
VS	0.974
RP-HP	0.924
HS	0.850

Extraction Method: Principal Component Analysis
(a). 1 component extracted

Table A6 contains component loadings, which are the correlations between the variable and the component, which are the correlations whose possible values range from -1 to +1.

Table A7
Component Score Coefficient Matrix[a]

	Component
	1
USW	0.179
EC	0.170
ES	0.181
VS	0.181
RP-HP	0.156
HS	0.182

Extraction Method: Principal Component Analysis
(a). 1 component extracted

For each case and each component, the component score (Table A7) is computed by multiplying the standardized variable values by the component score coefficients. In this case, the coefficients are applied to each standardized variable (*Z*-score) for each municipality with only a 9% loss of information.

Appendix B. Regression.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,99468332
R Square	0,989394906
Adjusted R Square	0,98931162
Standard Error	33373827,85
Observations	771

ANOVA

	df	*Sum Square*	*Mean Square*	*F*	*Significance F*
Regression	6	7,9389E+19	1,32315E+19	11879,47536	0
Residual	764	8,50953E+17	1,11381E+15		
Total	770	8,024E+19			

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