ENVIRONMENTAL QUALITY AND THE HUMAN DEVELOPMENT INDEX IN MINAS GERAIS (BRAZIL)

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Abstract

The terms 'environmental quality' and 'quality of life' are not synonyms. The applied socioeconomic analysis should consider variables that capture the environmental quality level in addition to the traditional ones. This study develops an HDI for the Minas Gerais municipalities considering environmental quality as one of its dimensions and checking each region rank position. A Principal Component Analysis on the Income HDI_M, the Longevity HDI_M, the Education HDI_M, and the Environment HDI_M (established in this study). The Expanded HDI_M shows that the environmental dimension reduces the human development level. A substantial change in the regions' position is not observed.

Keywords: environmental quality, Principal Component Analysis, Human Development Index.

Área temática*: 2. *TEORIA ECONÔMICA E ECONOMIA APLICADA

Acknowledgment

This paper was carried out with the support of the *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior* (*CAPES*) - Financing Code 001. The authors also thank the Brazilian National Council for Scientific and Technological Development (in Portuguese, *Conselho Nacional de Desenvolvimento Científico e Tecnológico* - *CNPq*) (case 306647/2015-0).

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1. Introduction

The environmental quality and quality of life concepts are difficult to define. Although they are closely related, they are indeed substantially different concepts. According to Mazetto (2000), environmental quality relates to the ecosystem basic conditions and requirements, whether biological, physical, chemical, economic, political, social or technological. On the other hand, quality of life is defined as the individual's perception of his or her position of life in the cultural context and the system of values in which he or she lives, his or her objectives, expectations, standards, and concerns (World Health Organization Quality of Life – WHOQOL – Group 1995). This concept is quite broad, thus interrelating the environment with physical, of independence level, of social relations, of personal beliefs, and psychological aspects for complexity and difficulty in terms of consensus. Then, it is clear the interaction between quality of life and environmental quality, since life and environment are inseparable.

Given the relation between those two different concepts exposed above and the context of increasing environmental degradation and the current concern about the environment, it is urgent to insert variables that capture the environmental quality (or its lack) in any economic and social applied analysis, which usually already consider factors related to income, education, and health. Despite the complexity of electing and creating variables that are effectively able to represent environmental degradation, there is a consensus indicating the anthropic pollutants emission as one of the main engines for the current environmental problems (Costa *et al*. 2011). Therefore, several countries already seek viable alternatives to reduce greenhouse gas emissions (Costa *et al*. 2011).

The Report on Human Development (RHD) in Brazil (in Portuguese, *Relatório sobre o Desenvolvimento Humano – RDH – no Brasil*), elaborated by the Brazilian Institute for Applied Economic Research (in Portuguese, *Instituto de Pesquisa Econômica Aplicada – IPEA*), as many studies that require a measurement of national development, is based on the Human Development Index (HDI). This index is drawn up by the United Nations (UN) and is a summary measure of the long-term progress of three basic dimensions of human development: income, education, and health. When it was created, the HDI aimed to offer a counterpoint to another widely used indicator, the Gross Domestic Product (GDP) *per capita*, which considers only the economic dimension of development. And, until the present day, it fulfills this goal by being a measure of economic production only. As recognized by its own creators – Mahbub ul Haq with the collaboration of the Indian economist Amartya Sem –, the HDI, despite expanding the perspective on human development, does not cover all aspects of development. It is neither a representation of the people's "happiness", nor indicates "the best place in the world to live" (United Nations Development Programme – UNDP – 2015). The United Nations Development Programme (UNDP) presents that democracy, participation, equity, and sustainability are other aspects of human development that are not covered by the HDI (UNDP 2015). Let it be done, then, as recommended, and add new human development dimensions to existing indices, thus creating more complete and adequate ones.

The resolution of this economic problem is important to the extent that it supplies a need for improvement and constant evolution of the analysis and research instruments. The measure of environmental sustainability offers additional analysis of the profile, potentialities, and limitations of human development, as suggested by the creators of the HDI and by Martins *et al*. (2006).

In general, there are few studies and scarce methodological options yet, especially in Brazil, to analyze environmental quality. Perhaps a work the most like this paper is the one carried out by Rossato (2006). But, in addition to the fact that it was about municipalities in the Rio Grande do Sul, its municipal environmental quality index does not include specific data on greenhouse gases (GHGs) emissions. Similarly, Martins *et al*. (2006) do not do an effort equal to this one because it deals with the countries' development and uses the Environmental Sustainability Index (ESI), which differs from our one. Rufino (2002) analyzes the environmental quality of a specific municipality: Tubarão, in the Santa Catarina state. However, the author built an environmental indicators system based on the pressure-state-response framework in order to do that, unlike the one that we performed. Regard the perspective of environmental degradation, few studies in Brazil quantify this degradation level for a region or state. We might cite Lemos (2001), which determined the environmental degradation level for the municipalities in the Northeast region, and Silva and Ribeiro (2004), which determined the degradation level for the municipalities in Acre state. However, none of them have the same systematic quantification of environmental degradation used here. Remember that the consensus points to the anthropic pollutants emission as one of the main engines for the current environmental problems (Costa *et al*. 2011).

Then, the purpose of this paper is to conduct an analysis of the development of the Minas Gerais regions, considering the environmental perspective, through the elaboration of two new indexes: the Environment Municipal Human Development Index (HDI_{EnM}) and the Expanded Municipal Human Development Index (HDI_{ExM}) in 2010. The idea is, besides the already considered quality of life, to seek to fill the gap left by the available development indexes inserting the difficult measurement of environmental quality in such indices.

The HDI_{EnM} is an environmental quality index. It is built here using GHG emission specific data. The municipality with the highest HDI_{EnM} is the one that emits less. The HDI_{ExM} is built considering, in addition to the three dimensions of human development considered by the original HDI (income, longevity/health, and education), the environmental dimension of development. For this purpose, a Principal Component Analysis (PCA) is performed on the four HDI_M: the Income HDI_M (HDI_{InM}), the Longevity HDI_M (HDI_{LoM}), the Education HDI_M (HDI_{EdM}), and the HDI_{EnM}. It is important to make it clear that the last of these indexes will be created in the present study, through prior PCA on the data about municipal GHG emissions for the 853 Minas Gerais municipalities.

Part of this work pioneering is the use of three different GHGs emissions data – carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) –, at municipal levels, in the representation of the environmental quality of the municipalities. Previous studies that also built environmental quality indexes did not have the opportunity to use data with such specificity.

Although this research is of universal interest when it is a possibility of increasing HDI robustness, it will benefit the most the Minas Gerais state's population. Because, throughout this work, Minas Gerais will have a ranking and an HDI considering the environmental issue for all its municipalities. In addition, a regional analysis of the state is made, which allows the observation, via comparison, of where are the largest bottlenecks of state development.

Thus, what follows is a brief presentation of the methodology and of the data. In the end, the results are discussed and the conclusions are posted.

2. Methodology

The methodology used was the Principal Component Analysis (PCA). The PCA is a multivariate analysis technique that consists of transforming an original set of variables, via a linear transformation operated in this set, into another set. The Principal Components (PCs) with specific properties, such as orthogonality (statistical independence) of the variables in this new set. According to Haddad (1989), this is a method to reduce the number of variables (from p to r, with $r < p$).

The resulting variables are called principal components. The PCs are linear combinations (weighted average) of the original variables defined in order to capture the maximum variance of the data. The estimation process is such that the first PC captures as much variance as possible, the second captures as much as possible from the remainder variance, the third as much as possible from the remainder variance, and so on. The PC is a new variable (an index) that represents a data's "dimension" (Haddad 1989).

According to Haddad (1989), this method has two basic objectives. The first is econometrical and the other one related to urban and regional analysis. In econometrics, the PCA is used when the explanatory variables have a high correlation degree (which makes the estimation of the estimates of the equation parameters' variances more difficult, preventing hypothesis tests on the estimated parameters' significance). Thus, this method creates variables that have correlations equal to zero, i.e., variables that satisfy the hypothesis of independence in linear regression (multicollinearity absence). In the urban and regional analysis, the method is used to classify regions and cities. This is possible via the creation of an index that allows their hierarchization.

In this paper, the PCA is applied to reach that last result: the regional classification. Our matrix has 853 rows, corresponding to the municipalities of Minas Gerais state, and seven columns, corresponding to the environmental and socioeconomic indicators in 2010 (Table 1).

Table 1 – Environmental and socioeconomic indicators used

Variable	Description
CO_2	Municipal CO_2 emission (weighted by area) in tons per square kilometer
CH_4	Municipal CH_4 emission (weighted by area) in tons per square kilometer
N_2O	Municipal N_2O emission (weighted by area) in tons per square kilometer
HDI_{InM}	Income Municipal Human Development Index
HDI_{LoM}	Longevity Municipal Human Development Index
HDI_{EdM}	Education Municipal Human Development Index
HDI_{EnM}	Environment Municipal Human Development Index

The Environment Municipal Human Development Index (HDI_{EnM}) was created in this work, via a first model, which considers those 853 rows and the first three variables reported above as its columns. It is just the first PC obtained by this model after transformed to the first quadrant. Thus, it becomes the fourth column of a second model which, besides considering those 853 rows, considers the three columns of the original HDI_M.

In this research, then, the PCA methodology is used twice. The first is in order to build an emission index, which generates, after a transformation, the Environment HDI_M. The second is in order to create the new HDI (the one that will also consider this environmental dimension in its construction): the HDI_{ExM}.

We transformed the first PC of the first model to the first quadrant in order to generate an index that allocates higher values for the municipalities that emit less GHG. The first step was to change its signal. Then, we determined the highest and the lowest emission index and calculated the amplitude between them. After these calculations, and in order to ensure that all values of this index would be in the first trigonometric quadrant, we took the values for each municipality (changed signal) and subtracted from them that lower value. Then, we divided the result by the amplitude.

Thus, these are the models for both PCA:

$$X_1 = a_{11}CO_2 + a_{12}CH_4 + a_{13}N_2O \quad (1.1)$$
$$X_2 = a_{21}CO_2 + a_{22}CH_4 + a_{23}N_2O \quad (1.2)$$
$$X_3 = a_{31}CO_2 + a_{32}CH_4 + a_{33}N_2O \quad (1.3)$$

$$Y_1 = b_{11}HDI_{InM} + b_{12}HDI_{LoM} + b_{13}HDI_{EdM} + b_{14}HDI_{EnM} \quad (2.1)$$
$$Y_2 = b_{21}HDI_{InM} + b_{22}HDI_{LoM} + b_{23}HDI_{EdM} + b_{24}HDI_{EnM} \quad (2.2)$$
$$Y_3 = b_{31}HDI_{InM} + b_{32}HDI_{LoM} + b_{33}HDI_{EdM} + b_{34}HDI_{EnM} \quad (2.3)$$
$$Y_4 = b_{41}HDI_{InM} + b_{42}HDI_{LoM} + b_{43}HDI_{EdM} + b_{44}HDI_{EnM} \quad (2.4)$$

where X_i, with, $i = 1, 2,$ and 3, are the three independents PCs that linearly describe the three observed variables – CO_2, CH_4, and N_2O – and the a_{ij}, with $i = 1, 2,$ and 3 and $j = 1, 2,$ and 3, are the weights or loadings that compose the linear combination. Analogous, the Y_k, with $k = 1, 2, 3,$ and 4, are the four independents PCs that linearly describe the four observed variables – HDI_{InM}, HDI_{LoM}, HDI_{EdM}, and HDI_{EnM} – and the b_{zk}, with $z = 1, 2, 3,$ and 4 and $k = 1, 2, 3,$ and 4, are the loadings that compose the linear combination. The components' coefficients indicate the importance of a specific variable for that component. It is important to emphasize once again that the HDI_{EnM} is just the first PC generated in the first model, namely:

$$HDI_{EnM} = X_1 \text{ (transformed to the first quadrant).}$$

The PC model was chosen due to its simplicity and, at the same time, adequacy to this research problem. In practice, this method application, either in the first or in the second model, begins with the calculation of the correlation matrix for the observed variables. The R_1 and R_2 matrices show the correlation coefficients between the variables observed, respectively, in Model 1 and Model 2.

$$R_1 = \begin{bmatrix} r_{CO_2CO_2} & r_{CO_2CH_4} & r_{CO_2N_2O} \\ r_{CH_4CO_2} & r_{CH_4CH_4} & r_{CH_4N_2O} \\ r_{N_2OCO_2} & r_{N_2OCH_4} & r_{N_2ON_2O} \end{bmatrix}$$

$$R_2 = \begin{bmatrix} r_{HDI_{InM}HDI_{InM}} & r_{HDI_{InM}HDI_{LoM}} & r_{HDI_{InM}HDI_{EdM}} & r_{HDI_{InM}HDI_{EnM}} \\ r_{HDI_{LoM}HDI_{InM}} & r_{HDI_{LoM}HDI_{LoM}} & r_{HDI_{LoM}HDI_{EdM}} & r_{HDI_{LoM}HDI_{EnM}} \\ r_{HDI_{EdM}HDI_{InM}} & r_{HDI_{EdM}HDI_{LoM}} & r_{HDI_{EdM}HDI_{EdM}} & r_{HDI_{EdM}HDI_{EnM}} \\ r_{HDI_{EnM}HDI_{InM}} & r_{HDI_{EnM}HDI_{LoM}} & r_{HDI_{EnM}HDI_{EdM}} & r_{HDI_{EnM}HDI_{EnM}} \end{bmatrix}$$

where $r_{CO_2CH_4}$ is the correlation coefficient between CO_2 and CH_4. The other coefficients interpretation can be made by analogy to this example.

These R_i are symmetric square matrices (e.g. $r_{CO_2CH_4} = r_{CH_4CO_2}$), and in their main diagonals, we will always find 1. Because the correlation between a variable with itself is always equal to 1:

$$R_1 = \begin{bmatrix} 1 & r_{CO_2CH_4} & r_{CO_2N_2O} \\ r_{CH_4CO_2} & 1 & r_{CH_4N_2O} \\ r_{N_2OCO_2} & r_{N_2OCH_4} & 1 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 1 & r_{HDI_{InM}HDI_{LoM}} & r_{HDI_{InM}HDI_{EdM}} & r_{HDI_{InM}HDI_{EnM}} \\ r_{HDI_{LoM}HDI_{InM}} & 1 & r_{HDI_{LoM}HDI_{EdM}} & r_{HDI_{LoM}HDI_{EnM}} \\ r_{HDI_{EdM}HDI_{InM}} & r_{HDI_{EdM}HDI_{LoM}} & 1 & r_{HDI_{EdM}HDI_{EnM}} \\ r_{HDI_{EnM}HDI_{InM}} & r_{HDI_{EnM}HDI_{LoM}} & r_{HDI_{EnM}HDI_{EdM}} & 1 \end{bmatrix}$$

In mathematical terms, we can find the loadings, which satisfy the conditions of orthogonality and of total variation explained by the CPs, through solving the following systems of homogeneous equations:

$$\begin{bmatrix} 1-\lambda & r_{CO_2CH_4} & r_{CO_2N_2O} \\ r_{CH_4CO_2} & 1-\lambda & r_{CH_4N_2O} \\ r_{N_2OCO_2} & r_{N_2OCH_4} & 1-\lambda \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{12} \\ a_{13} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 1-\lambda & r_{HDI_{InM}HDI_{LoM}} & r_{HDI_{InM}HDI_{EdM}} & r_{HDI_{InM}HDI_{EnM}} \\ r_{HDI_{LoM}HDI_{InM}} & 1-\lambda & r_{HDI_{LoM}HDI_{EdM}} & r_{HDI_{LoM}HDI_{EnM}} \\ r_{HDI_{EdM}HDI_{InM}} & r_{HDI_{EdM}HDI_{LoM}} & 1-\lambda & r_{HDI_{EdM}HDI_{EnM}} \\ r_{HDI_{EnM}HDI_{InM}} & r_{HDI_{EnM}HDI_{LoM}} & r_{HDI_{EnM}HDI_{EdM}} & 1-\lambda \end{bmatrix} \begin{bmatrix} b_{11} \\ b_{12} \\ b_{13} \\ b_{14} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

For these systems equations to have a non-trivial solution, i.e., for the loadings not to be equal to zero, it is necessary that the matrices do not have an inverse, that is, it is necessary that

$$|R - \lambda\, I| = 0$$

where I represents the unit matrix, and 0 the scalar zero. This is the characteristic equation, where λ is the characteristic vector associated with the characteristic matrix $(R - \lambda\, I)$. Fortunately, there is no need to solve a high-grade polynomial equation "by hand" because there is software able to extracting the characteristic roots and calculating the characteristic vectors associated with them. STATA 13 was the software used to estimate the PCs. Those characteristic vectors mentioned above are exactly the weights (loads) to be related to the variables in the linear transformation process that creates the PCs.

The importance of a specific PC is measured via the calculation of the proportion of the R matrix's total variation that may be attributed to this PC (Haddad 1989). The fact that the R's total variation is equal to the number of observed variables may be proved. This proportion is calculated as follows:

$$\frac{\lambda_1}{\text{n\# of observed variables}} \,.\, 100$$

The result is the share of the variables' correlation coefficients variation (percentage) that the first PC can reproduce. The number of characteristic roots (λ) is always equal to the number of variables. In this study, three and four in Models 1 and 2 respectively. However, it is not necessary to extract and work with all PCs because the first extracted one may be able to reproduce a large portion of the R's total variation. This is one of the PCA's advantages. It is easy to see that the second PC's extraction procedure is similar, using the matrix of the remaining correlation though. The same goes for the third and the other if they exist.

It is necessary to test the significance of the PCs' loadings. There are some tests available, but a practical rule is often used. It says that only loadings with an absolute value greater than 0.3 should be retained when we have at least 50 variables' observations. Thus, as we have 853 observations, we use this rule to verify if some loading is non-significant, i.e., if we should not reject the hypothesis saying that they are null.

Our last question so far, which is always raised, is about the number of PCs to be extracted. Haddad (1989) mentions that there are some criteria to make that decision. However, the practical rule is to keep analyzing only those components for which the characteristic root (λ) is greater than 1 when the number of variables is between 20 and 50. This is not the rule for us then. When we are not in this interval (this paper has, at first, three variables and, secondly, four), it is better to be guided by the proportion of the total variation associated with the first extracted components.

In order to have data referring to the Minas Gerais' 10 planning regions, we considered the average of the data referring to each region's municipality. The data used here, which contains the selected municipal development indexes, comes from the Atlas of Human Development in Brazil (2013). GDP data for the Minas Gerais' municipalities, which are used in the analysis of the development of the Minas Gerais' mesoregions, is from the Central Bank of Brazil's Regional Bulletin (2013).

Regarding the GHG data, we collected it from the Emission Database for Global Atmospheric Research – EDGAR (Joint Research Centre – JRC, PBL Netherlands Environmental Assessment Agency – PBL NEAA 2011). The EDGAR provides global and georeferenced data, i.e., with geographic coordinates, of several GHG emissions. The three ones used in this study are among them, in grids of 0.1º by 0.1º. The database is the latest from EDGAR (v4.2 FT2010) at the time this paper has been written and provides information between the years 2000 and 2010. The grid points were united to the municipal boundaries using their latitude and longitude coordinates, generating the annual averages municipal emissions of the gases (CO_2, CH_4, and N_2O) via the software ArcGIS (version 10.1). Such information was extracted in kilograms per square meter per second (kg/m²/sec). We used Equation 3 to transform the data into tons per square kilometer per year (ton/km²/year) as it follows:

$$\mathrm{e}_{\mathrm{j,m,t}_{\mathrm{ton/km^2/year}}} = \mathrm{e}_{\mathrm{j,m,t}_{\mathrm{kg/m^2/sec}}} \left(\frac{1}{1{,}000}\right)(1{,}000{,}000)(12{,}614{,}400) \tag{3}$$

where $\mathrm{e}_{\mathrm{j,m,t}_{\mathrm{ton/km^2/year}}}$ represents the gas j total emission in the municipality m at the year t measured in the tons per km², and $\mathrm{e}_{\mathrm{j,m,t}_{\mathrm{kg/m^2/sec}}}$ represents the average gas j emission in the municipality m at the year t measured in kg per m² per second. We calculated the annual total municipal emission (Equation 4) as well:

$$\mathrm{e}_{\mathrm{j,m,t}} = \mathrm{e}_{\mathrm{j,m,t}_{\mathrm{ton/km^2/year}}}(\mathrm{area}_{\mathrm{m}_{\mathrm{km^2}}}) \tag{4}$$

where $\mathrm{e}_{\mathrm{j,m,t}}$ refers to the total gas j emission in the municipality m at the year t, $\mathrm{e}_{\mathrm{j,m,t}_{\mathrm{ton/km^2/year}}}$ represents the gas j emission in the municipality m at the year t measured in tons per km², and $\mathrm{area}_{\mathrm{m}_{\mathrm{km^2}}}$ represents the area of the municipality m measured in km².

3. Results

We sought to estimate and build an index to indicate the level of human development in the Minas Gerais state, considering besides the economic and social ones, the environmental dimension. This study created an environmental quality index (HDI_{EnM}) for the 853 Minas Gerais' municipalities off the emitted level (weighted by the municipal area) of three GHGs (CO_2, CH_4, and N_2O). Thus, it was possible to create a new HDI, which considers the environmental dimension of human development, through this index built previously allied to those already used in the construction regular HDI. The Principal Component Analysis was performed in the construction of both indexes. Then we calculated the score of each city based on this last general index, using the loadings provided by the method. We established a hierarchy of the state planning regions based on these scores, obtaining the relative position of each of them in terms of the new HDI levels created for their cities.

We first collected the data on the environmental quality indicators of those cities: CO_2, CH_4, and N_2O emission levels by the municipality. This data, collected from the Emission Database for Global Atmospheric Research – EDGAR (Joint Research Centre – JRC, PBL Netherlands Environmental Assessment Agency – PBL NEAA 2011), were weighted by the area of the municipalities and were then measured in tons per square kilometer. The PCA initially led to the following results (Table 2):

Table 2 – Statistics for the Principal Components Analysis in Model 1

	X_1	X_2	X_3
Characteristic root (λ)	1.99	0.85	0.16
% of total variance	66.41	28.17	5.42
Accumulated % of total variance	66.41	94.58	100

Source: estimation's results.

The solution provides three PCs because it has three variables. The first PC (X_1) reproduces 66.41% of the total variation, i.e., this first component fairly synthesizes the information contained in the three environmental quality indicators for the municipalities. Therefore, there was a great deal of redundancy among those variables. The coefficients of the linear combinations, that form the PCs, are the elements of the characteristic vectors. The percentage of not explained variance is zero because three components were calculated, i.e., three components capture all the variance of the three variables. Thus, the three equations of the PCs obtained via the correlation matrix (with the standard errors for the coefficients of the characteristic vectors placed below):

$$\mathrm{X}_1 = 0.3737\ \mathrm{CO}_2 + 0.6463\ \mathrm{CH}_4 + 0.6653\ \mathrm{N}_2\mathrm{O} \tag{5.1}$$
$$\qquad (0.0358) \qquad (0.0146) \qquad (0.0109)$$
$$\mathrm{X}_2 = 0.9234\ \mathrm{CO}_2 - 0.3271\ \mathrm{CH}_4 - 0.2008\ \mathrm{N}_2\mathrm{O} \tag{5.2}$$
$$\qquad (0.0146) \qquad (0.0281) \qquad (0.0290)$$
$$\mathrm{X}_3 = 0.0878\ \mathrm{CO}_2 + 0.6894\ \mathrm{CH}_4 - 0.7191\ \mathrm{N}_2\mathrm{O} \tag{5.3}$$
$$\qquad (0.0176) \qquad (0.0092) \qquad (0.0080)$$

All the variables were statistically different from zero in all three components even if considering the significance level as 1%. The Mardia mSkewness, Mardia mKurtosis, Henze-Zirkler, and Doornik-Hansen tests for multivariate normality were performed and all of them rejected the null hypothesis of multivariate normality.

Using the loadings (i.e., the elements of the characteristic vectors related to each of the characteristic roots) of each variable and the municipal value for each of the three variables, the score (the value of X) was obtained for each of the 853 cities in X_1, X_2, and X_3. Then, we calculated the simple linear correlation coefficient between the X_i values and the values of each of those three environmental quality indicators. Table 3 shows the calculated values for the correlation.

Table 3 – Indicators and components' correlation coefficients in Model 1

Environmental quality indicators	Principal components		
	X_1	X_2	X_3
CO_2 emitted per square kilometer at 2010 measured in tons	0.53	0.85	0.04
CH_4 emitted per square kilometer at 2010 measured in tons	0.91	-0.30	0.28
N_2O emitted per square kilometer at 2010 measured in tons	0.94	-0.18	-0.29

Source: estimation's results.

As the correlation coefficients between the environmental quality indicators and the CP X_1 were high for two of them, X_1 is interpreted as a general index of environmental quality. Although X_2 has a high correlation with the first variable, it is not necessary to extract it, as the loading of this variable in X_1 was greater than 0.3 and this first CP is able to reproduce well (66.41%) the total variation. This according to that practical rule dealt within the methodology section.

Then, only one component does not explain all the data's variance, which occurs when three components are extracted. The first component explains 27.82% of the variance of the CO_2 variable, 83.23% of the variance of the CH_4 variable, and 88.18% of the variance of the N_2O variable. Note that the solution with only one component provides the same coefficients as the three-component solution. This is characteristic of the method.

It is necessary to remember that this environmental quality index must suffer a transformation because it assigns higher values to those cities that emit the most. Then, the fourth variable of the Model 2 – HDI_{EnM} – is the X_1 index with the changed signal and the transformation into the first quadrant. The HDI_{EnM} was built from the X_1 scores not only because it is a great association with most indicators of environmental quality, but also because of its explanation power in terms of the total variation (66.41%).

The scores calculated via PCA are always on an ordinal scale and can indicate the relative position of the cities only. In addition, as the HDI_{EnM} suffered a transformation to the first quadrant, we have zero values for the city with the lowest environmental quality (Belo Horizonte, Central region) and 1 for the one with the highest quality (Leme do Prado, Vales do Jequitinhonha e Mucuri region). The HDI_{EnM} shows a clear relationship between this index and the regional characteristics, being the Central and Triângulo regions the ones with worst indexes of environmental quality, while Alto Paranaíba and Vales do Jequitinhonha e Mucuri presented the best environmental results.

These results are easily justified when analyzing the map of the Minas Gerais' economy, which showed almost continuous growth (interrupted during the recession between 2008 and 2009 only, when there was a significant decrease in its GDP). The metropolitan region of Belo Horizonte alone concentrates 45% of the Minas Gerais' economic activities and it is also one of the regions that present the highest growth. The capital of Minas Gerais has 43% of the regional economic activities, followed by Betim and Contagem. The next regions are the Triângulo Mineiro, Alto Paranaíba, Sul e Sudeste de Minas, Zona da Mata and Vale do Rio Doce that together correspond to about 40% of the Minas Gerais' GDP. The least developed mesoregions are those in the Vales do Jequitinhonha e Mucuri which together have only 2.1% of the Minas Gerais's GDP according to the Central Bank of Brazil (2013).

We used the same method to build Model 2 of this study. Now, it is about four variables though. Three of them are from the data in the Atlas of Human development (HDI_{InM}, HDI_{LoM}, and HDI_{EdM}) and the fourth was built in this work (HDI_{EnM}) as above.

We were able to extract up to four PCs Y_i (Table 4), applying the method to the correlation matrix for the four variables (symmetric correlation matrix from which the eigenvalues and the eigenvectors may be obtained). The solution provides four PCs because we have four variables. The first PC (Y_1) reproduces 63.31% of the total variation, which means that this component fairly synthesizes the information level of the four HDIs for the municipalities of Minas Gerais. Therefore, there was a great redundancy among those variables. The characteristic vectors have the coefficients of the linear combinations that form the PCs as their elements. The not explained variance percentage is zero because four components were calculated, i.e., four components capture all the variance of the four variables.

Table 4 – Statistics for the Principal Components Analysis in Model 2

	Y_1	Y_2	Y_3	Y_4
Characteristic root (λ)	2.53	0.87	0.42	0.19
% of total variance	63.31	21.63	10.41	4.65
Accumulated % of total variance	63.31	84.94	95.35	100

Source: estimation's results.

Thus, the four PCs' equations obtained through the correlation matrix (with the standard errors for the coefficients of the characteristic vectors placed below) are:

$$\underset{}{Y_1} = \underset{(0.0090)}{0.5839\ HDI_{InM}} + \underset{(0.0138)}{0.5411\ HDI_{LoM}} + \underset{(0.0140)}{0.5295\ HDI_{EdM}} - \underset{(0.0289)}{0.2932\ HDI_{EnM}} \quad (6.1)$$

$$Y_2 = \underset{(0.0248)}{0.1177\ HDI_{InM}} + \underset{(0.0332)}{0.2694\ HDI_{LoM}} + \underset{(0.0403)}{0.1200\ HDI_{EdM}} + \underset{(0.0098)}{0.9482\ HDI_{EnM}} \quad (6.2)$$

$$Y_3 = \underset{(0.0345)}{-0.1433\ HDI_{InM}} - \underset{(0.0272)}{0.5809\ HDI_{LoM}} + \underset{(0.0151)}{0.7970\ HDI_{EdM}} + \underset{(0.0439)}{0.0819\ HDI_{EnM}} \quad (6.3)$$

$$Y_4 = \underset{(0.0086)}{0.7904\ HDI_{InM}} - \underset{(0.0252)}{0.5451\ HDI_{LoM}} - \underset{(0.0334)}{0.2646\ HDI_{EdM}} + \underset{(0.0197)}{0.0902\ HDI_{EnM}} \quad (6.4)$$

All variables are statistically different from zero in all four components at 10% of the significance level. The Mardia mSkewness, Mardia mKurtosis, Henze-Zirkler, and Doornik-Hansen tests for multivariate normality were performed and all of them rejected the null hypothesis of multivariate normality.

Using the loadings (i.e., the elements of the characteristic vectors related to each of the characteristic roots) for each variable and the value for each one of the four variables in each city, we obtained the score (the value Y) for the 853 cities in Y_1, Y_2, Y_3, and Y_4. Then, we calculated the linear correlation coefficient between the Y_i values and the values of each of those four HDI_M. Table 5 shows the calculated correlations.

Table 5 – Indicators and components' correlation coefficients in Model 2

Municipal HDI	Principal components			
	Y_1	Y_2	Y_3	Y_4
HDI_{InM} 2010	0.93	0.11	-0.09	0.34
HDI_{LoM} 2010	0.86	0.25	-0.37	-0.23
HDI_{EdM} 2010	0.84	0.11	0.51	-0.11
HDI_{EnM} 2010	-0.47	0.88	0.05	0.04

Source: estimation's results.

The PC Y_1 is interpreted as an expanded (relatively to the regular one) HDI_M (HDI_{ExM}) because of the high enough correlation coefficients between the municipal human development indicators and the PC Y_1. Although Y_2 has a high correlation with the fourth variable, it is not necessary to extract it, as the loading of this variable in Y_1 is higher, in the module, than 0.3 and this first component is able to reproduce well (63.31%) the total variation. This is in accordance with that practical rule presented in the methodology section.

One component alone does not explain all the data's variance, which occurs when the four components are extracted. The first component explains 86.34% of the HDI_{InM} variable's variance, 74.14% of the HDI_{LoM} variable's variance, 70.99% of the HDI_{EdM} variable's variance, and 21.78% of the HDI_{EnM} variable's variance. Note that the solution with one component alone provides the same coefficients as the solution with four components. It is a method's characteristic.

The scores calculated via a PCA are always measured on an ordinal scale and, therefore, can indicate only the relative position of the cities. Besides, in order to rank with values ranging from 0 to 1, we used a transformation to the first quadrant. This explains the 0 value for the town with the lowest human development (Setubinha, in the Vales do

Jequitinhonha e Mucuri region) and 1 for the most developed (Belo Horizonte, in the Central region). We perceived that even with high GHG emission indices (translated here into poor environmental quality) high-income, high-longevity, and/or high-education municipalities continue to appear in the best-ranking positions of the human development in Minas Gerais, even in the expanded, more comprehensive, and complete HDI_M (HDI_{ExM}).

When analyzing the 10 most developed in terms of the first PC (Y_1) of the Model 2 (transformed into the first quadrant), we perceived the predominance of cities in the Central and Sul regions of Minas Gerais (Table 6). The three cities out of these regions – Uberlândia, Ipatinga, and Viçosa – have obvious reasons to appear among the first ones in this index. Uberlândia is the second most populous municipality, after Belo Horizonte, and has the third largest HDI of the state, it is the largest wholesale pole in Latin America, with a privileged geographic location (its road network links it to the major national centers). Almost entirely urban, the development of Ipatinga is mainly due to the large companies of the so-called "Vale do Aço", economic and cultural hub, it has high HDI and is the most populous municipality of its microregion. Viçosa, in turn, has an educative vocation but presents high HDI as well.

Table 6 – Human development ranking for Minas Gerais (best placed)

Rank	Municipalities (MG)	Planning Region (MG)	HDI_{ExM}
1	Belo Horizonte	Central	1.000
2	Nova Lima	Central	0.757
3	Contagem	Central	0.661
4	Uberlândia	Triângulo	0.572
5	Itajubá	Sul de Minas	0.551
6	Lavras	Sul de Minas	0.547
7	Ouro Branco	Central	0.546
8	Varginha	Sul de Minas	0.540
9	Ipatinga	Rio Doce	0.536
10	Viçosa	Mata	0.536

Source: own elaboration.

A small city – Ouro Branco – figured among the first positions of the HDI_{ExM}, which does not happen in the regular ranking of HDI. This is an example of the environmental issue relevance in the analysis. Although Viçosa succeeded in overcoming Ouro Branco in the original HDI_M from 2000 to 2010, when the environmental issue is considered, Ouro Branco is still more developed than Viçosa. On the other hand, the 0.54 of Viçosa is greater than the 0.52 of Juiz de Fora (18^{th} position), a result not yet observed in the original HDI_M. In other words, when considering the environmental issue in the formulation of a new HDI_M, Viçosa goes beyond the largest and most developed city in the Zona da Mata – Juiz de Fora. These differences corroborate the need to observe other dimensions of human development, in addition to those three usually observed, in building scientific and academic thoughts.

At the opposite end of the ranking, the clear predominance is of cities belonging to the Vales do Jequitinhonha e Mucuri region. Six of the last 10 are in this region (Table 7). In general, even the low GHG emission levels at these municipalities were not able to withdraw them from the relatively poorly developed condition, such low ness of their social indicators.

Table 7 – Human development ranking for Minas Gerais (last placed)

Rank	Municipalities (MG)	Planning Region (MG)	HDI_{ExM}
844	Palmópolis	Jequitinhonha/Mucuri	0,040
845	Imbé de Minas	Rio Doce	0,036
846	Catuji	Jequitinhonha/Mucuri	0,027
847	Bonito de Minas	Norte de Minas	0,024
848	Mount Formoso	Jequitinhonha/Mucuri	0,019
849	Santa Helena de Minas	Jequitinhonha/Mucuri	0,017
850	Ladainha	Jequitinhonha/Mucuri	0,013
851	São João das Missões	Norte de Minas	0,011
852	Frei Lagonegro	Rio Doce	0,005
853	Setubinha	Jequitinhonha/Mucuri	0,000

Source: own elaboration.

We compared the planning regions of the Minas Gerais state as well. The result shows again some differences between the HDI_M and the HDI_{ExM} (Table 8).

Table 8 – Ranking for the planning regions of Minas Gerais, 2010

Rank (HDI_M)	Planning Region	Rank (HDI_{ExM})	Planning Region
1	Alto Paranaíba	1	Triângulo
2	Triângulo	2	Alto Paranaíba
3	Centro Oeste	3	Centro Oeste
4	Sul de Minas	4	Sul de Minas
5	Noroeste	5	Central
6	Central	6	Noroeste
7	Mata	7	Mata
8	Rio Doce	8	Rio Doce
9	Norte	9	Norte
10	Jequitinhonha/Mucuri	10	Jequitinhonha/Mucuri

Source: own elaboration.

Four regions did not change their positions when we added the environmental dimension in the expanded HDI_M. The environmental quality made the Triângulo Mineiro region take the first place off the Alto Paranaíba region and the Central the fifth position off the Noroeste de Minas region.

4. Conclusion

The association between environmental quality and quality of life is quite evident throughout the national territory and is not restricted only to specific regions or states. However, this study aimed to identify the association between socioeconomic conditions and environmental quality of the Minas Gerais' municipalities, highlighting aspects related to their planning regions. We also sought to quantify the environmental quality level of the Minas Gerais' municipalities and to build an alternative HDI, which considered an environmental component (the Expanded HDI_M) to reflect the level of human development in the studied municipalities. Our hypothesis was that the association between environmental quality and socioeconomic conditions in the state is lower environmental quality in municipalities with better economic conditions.

The methodology used to determine the association between environmental quality and quality of life was to analyze explanatory indicators of these qualities. The variables and indices were selected to represent the environmental quality and quality of human life. We used the Principal Component Analysis to build an environmental quality index – the HDI_{EnM} – and, subsequently, to make the ranking of the municipalities for the Expanded HDI. We could confirm via this methodological and practical effort that the PCA is even a good tool to reduce the number of variables in research. This is true mainly when using such a tool to build indexes and organize scores.

Thus, as to the problem treated in this study, we can say that success was achieved in terms of building our index using the aforementioned technique. We visualized – via the index and the ranking of municipalities and regions – the predominant positions of each of the state's planning regions. This result brings an alert mainly to the regions of the Vales do Jequitinhonha e Mucuri, Norte de Minas, and Vale do Rio Doce. In general, their municipalities are still distant from the results achieved by cities of other regions.

We also observed that small cities can visibly put themselves ahead of other major ones by the environmental issue. This means that sometimes the economic power is not enough to change a municipality into developed according to the expanded index due to poor environmental quality. We can say that the same occurs when analyzing at the regional level rather than municipal. Examples are the overcoming of the Triângulo de Minas and Central regions on those Alto Paranaíba and Noroeste de Minas ones.

The findings allow drawing some conclusions about the relationship between economic conditions and environmental quality at Minas Gerais in 2010. The Expanded HDI shows that the environmental dimension of the municipalities significantly reduces the level of human development. This scenario refers to the forms of development practiced in the regions of Minas Gerais and the importance of the inclusion of the environmental variable in the development models.

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