Including an environmental quality index in a demographic model

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Abstract

This paper presents a new well-being index which allows environmental quality to be measured through CO_2 emissions, renewable energies and nuclear power. Its formula derives from a geometric mean used to calculate which things in the human production system warm the planet and which do not. This index has been introduced into a gender-defined stochastic population dynamic mathematical model which measures well-being in a country. The main variables in this model are rates of death, birth, emigration and immigration, as well as three *UN* indices: Human Development Index, Gender Development Index and Gender Empowerment Index. This model has been extended with variables that allow an environmental quality evaluation, and it has been validated for Spain during the 2001-2010 period. Moreover, a sensitivity analysis has been carried on the simulated future trend (2011-2020) to see which environmental quality variables refer more to deaths, births or the Human Development Index.

Keywords: Environmental quality; demographic model; well-being.

1. Introduction

Programme 21 was forged in the United Nations Conference on Environment and Development (*UNCED*), which was held in Rio de Janeiro, Brazil, from 3 to 14 June 1992. This programme is an action plan that should be adopted universally, nationally and locally by organisations of the United Nations System, Governments, and major groups in all areas in which humans influence the environment. This paper focuses on Chapters 5 and 9 of Programme 21 to justify the need for an index that measures environmental quality.

Chapter 5, entitled Demographic Dynamics and Sustainability, proposes promoting "Increasing and disseminating knowledge about the relationship between demographic trends and factors and sustainable development", whose main objectives are:

a) Incorporating demographic trends and demographic factors into the global analysis of issues relating to the natural environment and development.
b) Better understanding the relationship among population dynamics, technology, cultural behaviour, natural resources and life support systems.

Chapter 9, entitled Protection of the Atmosphere, proposes the "Addressing uncertainties: improving the scientific basis for decision-making", among others. There is growing concern about climate change, climate variability and air pollution. Therefore, it is necessary to improve the understanding and predictability of the various properties of the atmosphere and those ecosystems affected, as well as effects on health and its interaction with socio-economic factors. The main objectives are:

a) Promoting sustainable development.
b) Reducing the harmful effects produced by the energy sector on the atmosphere by promoting policies or programmes, whenever appropriate, that increase the contribution of environmentally-sound and economical energy systems, in

particular new and renewable energies, through the production, transmission, distribution and use of cleaner and more efficient energy.

After studying Programme 21, we understand that the combination of world population growth, production and unsustainable consumption places enormous pressure on the Earth's ability to sustain life. If management is incorrect, rapidly growing cities will face major environmental problems, which will have economical, demographical, health, educational and environmental effects worldwide. The need for strategies that solve environmental problems has led us to the creation and proposal of an environmental quality index, and to introduce it into a population model that measures a country's well-being.

The literature contains demographic models that include CO_2 emissions. For example, Cranston and Hammond (2010) studied the impact of population size and economic growth on CO_2 emissions. This study was carried out in industrialised and overpopulated countries. These authors concluded that, although population growth influences the CO_2 concentration in the atmosphere, economic growth has a more significant impact on this phenomenon. Thus, this study significantly supports the objective of the present paper. The paper by Liddle and Lung (2010) included a population-based analysis (based on age, in this case), as well as CO_2 emissions caused by transport, residential energy and electricity consumption. It showed that the population's environmental impact differed between age groups as older age groups (50-64 years) had a negative influence. Moreover, Martinez and Maruotti (2011) analysed the impact of urbanisation on CO_2 emissions in developed countries during the 1975-2003 period. The results showed an inverted U-shaped relationship between urbanisation and CO_2 emissions. These authors divided countries into three groups and, for two of them, they observed that further increases in the urbanisation rate did not contribute to higher emissions. However, the third group, this being population and wealth, but not development, helped explain emissions.

In the same way, O'Neill et al. (2012a) studied the relationship between demographic change and CO_2 emissions. They provided results on how fossil fuel-based CO_2 emissions are affected by factors such as population growth or population decline, ageing, urbanisation and changes in household size. Their results led them to conclude that the policies which defend slow population growth will have climate-related benefits. O'Neill et al. (2012b) conducted a study on the implications that a range of possible development paths for the best energy use and for cutting CO_2 emissions in India and China will have. They found that changes in urbanisation had a slightly less proportional effect on aggregate emissions and energy use. They also demonstrated that this effect was due mainly to the economic growth driven by increased labour associated with rapid urbanisation.

Finally, Billionnet (2013) presented many examples of the mathematical models offered to protect biodiversity. The various chosen examples referred to the selection of nature reserves, controlling the adverse effects caused by landscape fragmentation (such as the creation or restoration of wildlife corridors), ecological forest management, controlling invasive species and maintaining genetic diversity. Most of these models represented the decisions made in a static context, but they also considered the time dimension. This work concluded that research is still required for progress to be made in protecting biodiversity and to successfully deal with real cases.

Our aim was to build a demographic dynamic model that includes some well-being indices defined by the United Nations (*UN*) in its Human Development Reports (*UNDP*, 1990-2011), such as Human Development Index (*HDI*), Gender Development Index (*GDI*) and Gender Empowerment Index (*GEM*), and an index that measures environmental quality in order to come closer to measuring the generic quality of a given country.

Basically, the *HDI* is a summary measure of the average achievement made in some key dimensions of human development: a long and healthy life, being knowledgeable and enjoying a decent standard of living. The *GDI* measures the gender gap in human development achievements in three basic dimensions of human development (health, education and command) over economic resources. Finally, the *GEM* is a measure of inequalities between men's and women's opportunities in a given country.

To go about accomplishing our aim, we found some particularly interesting papers that have worked with the three well-being indices listed above. Caselles et al. (2008) and Sanz et al. (2011) proposed two deterministic human population-dynamics models using these three indices; the second model is more complex and has been validated for Belgium for the 1997-2008 period. Sanz et al. (2014a) presented a stochastic human population-dynamics model per gender, in which fertility and death rates depended on the *GDI*. The model has been validated for Spain for the 2000-2006 period and has been applied to select government investments for the 2006-2015 period. Finally, Sanz et al. (2014b) also offered a gender-defined stochastic model, but birth and death rates depended on *HDI*, *GDI* and *GEM*. It has been validated for Austria for the 1999-2009 period and has been applied to solve the population stability problem.

The present paper is based on the model developed by Sanz et al. (2014b). First, we introduced into that model the necessary variables and functions to take into account environmental quality. Then we designed a generic formula, which has been validated for Spain. It allows the measurement of the level of environmental quality through not only CO_2 emissions, but also by using nuclear power and renewable energies. The new extended model has also been validated for Spain and has been applied to shed some light on this problem.

It is necessary to emphasise the fact that the environmental quality index is calculated from the CO_2 emissions produced by using energies. The work by Budzianowski (2013) supported this approach as he asserted that "It is likely that changes in the energy sector will play a central role in climate change mitigation strategies".

Nuclear power and renewable energies have also been introduced into this index. On the one hand, nuclear power is not the full answer to global warming problems, but it does not produce carbon emissions (Blix, 1990). Zakaria (2014) explained that nuclear power can be cheaper than other energies, but its production is more expensive and its radiation might be a potential threat to the environment. On the other hand, renewable energies have also been introduced because as the EPA (the United States Environmental Protection Agency) stated: "*Renewable energy is electricity generated by fuel sources that restore themselves over a short period of time and do not diminish. Although some renewable energy technologies have an impact on the environment, renewables are considered environmentally preferable to conventional sources and, when replacing fossil fuels, have significant potential to reduce greenhouse gas emissions.*" Bacher

(2002) concluded that renewable energies (with natural gas or nuclear power) are important energies in the 21st century.

From this point, this work is divided as follows: Section 2 presents and justifies the environmental quality index called *EQUI*. Section 3 introduces the *EQUI* variable into the demographic mathematical model. Section 4 validates the model in its deterministic and stochastic formulation for Spain during the 2001-2010 period. Section 5 offers a sensitivity analysis with simulated future trend data (2011-2020) to observe the relationship between environmental variables and deaths, births and the *HDI*. Finally, Section 6 presents some conclusions drawn from this work.

2. Environmental Quality Index

The Environmental Quality Index (*EQUI*) was calculated from three different variables that relate to the energy that a country consumes: CO_2 emissions, renewable energies and nuclear power. In turn, CO_2 emissions were calculated from using those energies that produce emissions, namely coal, oil and natural gas, and from those structures that mitigate these emissions, in this case, a forest area.

Figure 1 illustrates these relationships. Note that there are other variables involved that have not been considered, such as marine phytoplankton or details of all renewable energies (wind, hydro, solar, etc.). The used variables were those for which it was possible to acquire adequate real data to be used in the model. If we obtain more historical data on the aforementioned variables, these new variables will be introduced into the equations presented in this paper in the future.

(Please insert Figure 1 about here)

This section is divided into two parts: the first explains how CO_2 emissions are calculated from the influential variables according to Figure 1; the second reasons about the procedure used to calculate the *EQUI* index.

2.1. Study of the relationship between CO_2 emissions and the variables involved to calculate them

As seen in Figure 1, CO_2 emissions were calculated based on the use of coal, natural gas or oil. We also introduced a forest area because the larger the forest area, the lower the CO_2 emitted into the atmosphere. As the data had different magnitudes, the first step was to normalise all the variables used to calculate CO_2 emissions. To do this, the following equation was used, where *VARI* was a generic variable to be normalised:

$$VARI = \frac{real\ value - minimum\ value}{maximum\ value - minimum\ value} \qquad (1)$$

The required maximum and minimum values for our variables are presented in Table 1. The real CO_2 emission values were taken from the World Data Bank for the period considered (2000-2009). The maximum and minimum values were the maximum and minimum ones of the 247 countries for which information exists for the 1960-2009 period. The minimum value corresponded to Swaziland, for 1961, and the maximum one to the United Arab Emirates for 1969. This broad spectrum of countries and time were chosen to confer as much generality as possible to the new index.

Information on the real values of the other four variables shown in Table 1 was obtained from the Spanish National Statistics Institute (*INE*) for the 2000-2009 period, as Spain is the country where the model in this paper has been validated.

(*Please insert Table 1 about here)*

After normalising the data, the relationship between the dependent variable (CO_2 emissions) and all the independent variables that appear in Table 1 is graphically observed. Figure 2 illustrates this graphical relationship.

(*Please insert figure 2 about here)*

From this figure, no clear conclusion can be drawn: the upward trend was the logic for coal, oil and gas. It is possible that the downward part of the gas curve is because of gas replaces other energy sources that emit more CO_2; the upward part for the forest area is possible because its growth coincides with a period of general growth for the country's economy (more CO_2); the almost stable trend for coal is more difficult to explain. However *a priori,* it seems logical that the mathematical relationship between these independent variables and CO_2 emissions was a linear combination: each CO_2 source had an impact given its positive emission coefficient, except for the forest area where the coefficient was negative. This intuition was confirmed using the *Regint* functions' searcher (Caselles, 1998), with which the following equation was obtained as a valid function with a higher determination coefficient, random remainders and the Kolmogorov-Smirnov test passed (data normality):

$$co2e = 0.324705 + 0.0168638\, carb + 0.00966052\, gast + 0.0783131\, petr - 0.576634\, fosu \qquad (2)$$

where:
CO2E: CO_2 emissions;
CARB: coal;
GAST: natural gas;
PETR: oil;
FOSU: forest area.

In Figure 3, the randomness of the remainders for the fit of Equation (2) is shown, along with the determination coefficient (R^2), which was over 0.99 (R^2 is a useful index for measuring the overall degree of fit between two data sets), and the Kolmogorov-Smirnov test results. Thus, the CO_2 emissions variable was introduced into the model by Equation (2).

(*Please insert Figure 3 about here)*

2.2. Computing EQUI

As with the variables used to calculate CO_2 emissions, we did the same with the variables employed to calculate *EQUI* after normalising the real data. The information that we used is provided in Table 2.

In this case, information on the variables "nuclear power" and "renewable energies" for the 2000-2009 period was also obtained from the *INE* databases.

(*Please insert Table 2 about here)*

Equation (3) was used to calculate *EQUI*. Then we attempted to answer any questions about the design of this equation that could arise:

$$equi = \sqrt{\frac{\frac{0.2 \cdot co2e + 0.8 \cdot nucl}{reen}}{10}} \qquad (3)$$

where:
CO2E: CO_2 emissions;
NUCL: nuclear power;
REEN: renewable energies.

Note that the minimum value that variable *REEN* could take was 0.1. If it was not possible for a country to use renewable energies or their use took a value less than 0.1, then the 0.1 value for this variable was used in the formula by default.

What does EQUI measure? With this formula, we intended to aggregately measure the negative impact of human activity on the global ecosystem by taking the relationships between what warms and what does not warm the planet in the human production system as representatives. CO_2 warms the planet through the greenhouse effect (let's not forget the negative impact that any industrial activity producing CO_2 has directly or indirectly on the ecosystem). Nuclear power ends up being converted into heat through any human activity that it generates (including its well-known risks to the environment and the own negative impact of the human activity that it generates). It is assumed that renewable energies do not contribute, or they do so relatively poorly, to global warming and environmental degradation. *EQUI* was designed to vary between 0 and 1. A value closer to 0 implies reducing global warming. So it is well-accepted that we should use more renewable energies and less nuclear power, and we should reduce CO_2 emissions, just as the formula indicates.

Why a geometric mean? Firstly, let's recall that we are creating an environmental quality index. If we look at the literature on this subject, the Human Development Reports of the United Nations explain the creation of all the well-being indices that this organisation has developed. After the Human Development Report was published in 2010 (UNDP, 2010), almost all these indices were calculated with a geometric mean, which it justified by stating: "The geometric mean decreases the level of substitutability between dimensions [being compared] and at the same time ensures that 1 percent decline in life expectancy at birth has the same impact on the HDI as a 1 percent decline in education or income. Thus, as a basis for comparisons of achievements, this method is more respectful of the intrinsic differences across dimensions than the simple average." (http://hdr.undp.org/en/statistics/faq/). Finally, the geometric mean is often used to average percentages, indices and relative numbers by providing an average with an advantage over the arithmetic mean as it is not affected that much by extreme values.

Why take 0.2 and 0.8 as weights for CO_2 emissions and nuclear power? They are tentative values which were estimated based on existing literature. We know that CO_2 emissions are those that actually cause global warming and that nuclear power prevents around 700 million tons of CO_2 being emitted into the atmosphere each year. Therefore apart from its other known disadvantages and risks, its weight is heavier.

Note that the *CO2E/REEN* and *NUCL/REEN* ratios were averaged. Remember that variables *CO2E, NUCL* and *REEN* were normalised to between 0 and 1, and that it was assumed that the maximum value of any of these ratios was 10 because the maximum value of the numerator in both ratios was 1 and the minimum value of *REEN* was 0.1.

3. Introducing *EQUI* into a demographic model

The model used to introduce the environmental quality index was that created by Sanz et al. (2014b). This model contained four subsystems: demographic, educational, health and economic. The environmental subsystem was the novel aspect of this paper. It improved the model and proved useful to solve a wider range of problems. Figure 1 in Appendix 1 shows a Forrester Diagram (Forrester, 1961), which allows us to rapidly see the connections among all the variables that the model includes. Appendix 1 also presents some general explanations to better understand the Forrester Diagram, and it contains the list of all the model variables by specifying the type of each variable and its unit of measure.

Sanz et al. (2014b) calculated the birth and death rates from the multiplication of the well-being indices: *HDI*, *GDI* and *GEM*. We introduced the *EQUI* variable into these formulae. As *EQUI* varied between 0 and 1, and as the highest values corresponded to greater environmental deterioration, it seemed logical that it intervened by dividing instead of multiplying. Thus we defined variable *x* through Equation (4):

$$x = \frac{hdi \cdot gdi \cdot gem}{equi} \qquad (4)$$

Variable *x* was the independent variable in the formulae that we used to calculate the aforementioned rates (see Figures 4-7).

Sanz et al. (2014a, 2014b) had their reasons to choose the combination of a straight line with a cosine to fit the oscillation observed in the birth and death rates rather than using a combination of logistics which, according to Marchetti et al. (1996), would have been more appropriate for this particular case. To show that the formula was generic, i.e., valid for any country that we wish to study, these authors selected a countries sample (the countries belonging to the OECD, for which data were available). In our case, we used the combination of logistics. When introducing *EQUI* into the formulas, it was difficult to compare it with other countries because not all the data on nuclear power has been included in the World Data Bank; consequently, it was not possible to validate the rates for other countries. Therefore, we validated only for Spain, but perhaps we will attempt to validate the model for other countries in the future (when more information will be available).

Let's recall the shape of the logistic function and the interpretation of the values of its parameters:

$$variable(xx) = b0 + \frac{b1}{1+b2*\mathrm{Exp}[\mathrm{b3}*(xx-xx0)]} \qquad (5)$$

where *b0* can take any value, *b1*> 0 and *b3* <0 (to represent a logistic function), if *b2*> 0, it is a growing logistics; if *b2* <0, it is a decreasing logistics. Furthermore, *xx* can also be considered the time or any other variable, and *xx0* represents its initial value.

We present the logistics functions that fitted the real data corresponding to the birth and death rates per gender, and also the corresponding graphs (Figures 4-7).

(*Please insert Figures 4-7 about here)*

We can see in Figures 4-7 that introducing the *EQUI* variable into *x* increased not only the determination coefficient of the demographic rates, but also the level of randomness of the remainders as compared to the previous results reported by Sanz et al. (2014b). So we consider these equations to be valid.

4. **Model Construction and Validation**

We herein introduced environmental variables into a dynamic demographic mathematical model, which was previously used in the work by Sanz et al. (2014b). For this reason, we presented only the novel aspects, which were classified into three types: (a) the new input variables and their fit over time; (b) the relations of the new variables with the previous variables in the model; (c) the validation of the new extended model.

4.1. New input variables

Note that these new variables were those that represented the consumption of various energy types in one country and a forest area. As the model was continuously defined, these input variables should be fitted over time, and they were fitted by logistic functions because such trends have been observed (Marchetti et al., 1996).

Figure 8 shows the validation of these fittings. In this case, the logistics corresponding to each input variable are not shown.

(*Please insert Figure 8 about here)*

4.2. Relations between previously existing variables in the model and new ones

We observed that some of the input variables that corresponded to the economic subsystem could be related to energy consumption. For this reason, we introduced a new variable, *CONE*, which resulted from the addition of all the energies used.

$$CONE = carb + petr + gast + nucl + reen \tag{6}$$

Now we can graphically observe the trend among energy consumption, *CONE* and each economic input variable. Figures 9, 10, 11 and 12 show the real data. All these figures indicate a growing trend. Among the known functions that fitted growing trends, we once again chose logistics because, if it was of the growing kind (*b2*> 0 in Equation 7), it would have an asymptotic maximum. The generic form of this function is as follows:

$$variable(cone) = \mathrm{b0} + \frac{\mathrm{b1}}{1+\mathrm{b2}*\mathrm{Exp}[\mathrm{b3}*(cone - cone\ inicial)]} \tag{7}$$

With these fittings, the obtained determination coefficients were above 0.86. The residuals were also random and normally distributed (using the Kolmogorov-Smirnov test).

Figure 9 shows an increasing trend of the Final consumption expenditure (*GCFI*)

(*Please insert Figure 9 about here)*

Figure 10, which represents the Gross Capital Formation (*FBCA*), depicts no clear trend. Therefore, we considered that this variable was not in accordance with the energy used (although Logic suggests otherwise).

(*Please insert Figure 10 about here)*

In the case of Exports of Goods and Services (*EBSE*), Figure 11 indicates that the situation was similar to that of variable *GFCI*.

(*Please insert Figure 11 about here)*

Finally from Imports of Goods and Services (*IBSE*) in Figure 12, we deduced that the situation was similar to that of variables *GFCI* and *EBSE*.

(*Please insert Figure 12 about here)*

4.3.Validation of the new extended model

Model validation was presented with two formulations: deterministic and stochastic. The historical data, used to validate the model, were obtained from the *INE* database and covered the 2001-2010 period. *SIGEM* was the software tool employed for model validation (Caselles, 1998, 2008).

4.3.1. Deterministic Validation

The model was created as a set of differential and functional equations. Solutions were calculated with the Euler Method following Djidjeli et al. (1998), who explained that the Euler Method was more suitable for solving such equations. This approach resulted in a set of finite difference equations, which were programmed in Visual Basic 6.0 and were run using *SIGEM*. The obtained results corresponded to the 2001-2010 period.

Validation was done numerically by calculating the determination coefficients and the random remainders tests (Figure 13). The degree of overlapping of the results obtained for each year and the historical data were also graphically depicted. The validation process was considered successful because the determination coefficients, R^2, were very high, and the maximum relative error did not exceed 2.3% in any case.

(*Please insert Figure 13 about here)*

Note that in Figure 13 the model predictions presented a one-sided bias. This bias was considered negligible given the low maximum relative error value.

4.3.2. Stochastic validation

In addition to validating the model, its stochastic version was used to simulate the future because it helped determine the reliability of the results (each result was obtained with its respective confidence interval or its respective mean value and standard deviation).

The procedure used to verify that the stochastic model formulation was valid was:

1. Verifying that all the past simulation results showed a normal distribution (for this purpose, *SIGEM* automatically programmed a χ^2 test).
2. Obtaining each result with its respective confidence interval (e.g., 95%).
3. Checking that all the historical data fell within their respective simulated interval.

The results for the variables "female population" and "male population" for this validation type are respectively presented in Figure 14 and confirm that the model is valid for Spain for the 2001-2010 period.

(*Please insert Figure 14 about here)*

5. Application

As mentioned at the beginning of this paper, we used this model in an attempt to shed some light on an existing problem. In this case, a sensitivity analysis was applied to observe the direct relationship among births, deaths, the *HDI* and the input variables in a simulated future trend (the 2011-2020 period). We present only the main results in this section as the whole study is provided in Appendix 2.

The sensitivity analysis is contemplated herein as the study of the impact that a minor change in an input variable can have on an output variable by considering the model. Yet obviously, this output variable might also be affected by the remaining input variables. Thus for the purpose of noting the real effect of each input variable on the given output variable, we had to consider that the other input variables were constant or we had to take a random sample of all the possible combined values. Otherwise, as in the present case, the analysis would be valid for only the specific situation considered. An example of this approach is found in a work by Caselles et al. (1999).

Some methodological observations:

- The input variables were assumed independent.
- If the real data did not originate from a random sample taken from within the range of all the possible values for each input variable, the conclusions would be valid for only the particular situation considered.
- The future trend was simulated with the stochastic model and attempts were made to find the best direct relationship between each selected input variable and output variable.
- These data were fitted by linear and/or quadratic functions because, with these functions, it was easier to interpret their coefficients in relation to the sensitivity of the dependent variable in relation to the independent variable. In the linear function, $y = mx + n$, m gave the rate of increase or decrease of y in relation to x. In the quadratic function $y = ax^2 + bx + c$, this rate of increase or decrease was determined by its derivative function, $2ax + b$. The aforementioned rate was that which determined the degree of sensitivity of y in relation to x; that is, that which increased or decreased y for each unit of increase in x in general (for a linear fit) or at each point (for the parabola type fit).
- The R^2 coefficient determined the fraction of variability of the output variable, which was explained by the input variable with the considered function.

The variables relating to energy and the environment were the novel aspect of this model. So we paid attention to these input variables in an attempt to find direct relationships between them and births, deaths and the *HDI* with the previously presented methodology.

All the relationships between births and the energy variables considered in this work are summarised in Table 3 (more details are provided in Appendix 2).

(Please insert Table 3 about here)

Note that with variables *GAST* and *CARB*, no direct relations were found. Therefore we did not provide graphs and we did not analyse these cases.

(Please insert Figure 15 about here)

Relationship (8) is a parabola.

$$Births = -1.69567 \cdot 10^7 + 4.02469 \cdot 10^7 \cdot reen - 2.3185 \cdot 10^7 \cdot reen^2 \quad (8)$$

When interpreting these results, we see that renewable energies clearly related with births ($R2 = 0.91$). The resulting parabola from the fit to the simulated data was interpreted as follows (note that in all cases, the environment-related variables were normalised, so they took values of between 0 and 1):

1 - The potential impact associated with a possible variation in *REEN* was calculated using derivative function $2\ (-2.3185 \cdot 10^7)\ reen + 4.02469 \cdot 10^7$.

2 - The maximum value of simulated births (roughly 300,000 people) was associated with a renewable energies value, $REEN = -4.02469 \cdot 10^7 / (2\ (-2.3185 \cdot 10^7)) = 0.868$.

3 - As the simulated *REEN* values between 2011-2020 were between 0.84 and 0.94, an increase of one-thousandth in their lowest value was associated with variation in Births: $(2\ (-2.3185 \cdot 10^7)\ 0.84 + 4.02469 \cdot 10^7)\ 0.001 = 1296$, while the same increase in their higher value was associated with variation in Births: $(2\ (-2.3185 \cdot 10^7)\ 0.94 + 4.02469 \cdot 10^7)\ 0.001 = -3341$; that is, sensitivity of Births in relation to Renewable Energies would be great, and would be positive near the lower limit, negative near the upper limit, and very low near the value of 0.868.

4 - Using the same procedure, any intermediate value can be obtained.

Conversely for nuclear power (Figure 16), the relationship (9) was linear:

$$Births = 265642 + 630374 \cdot xucl \quad (9)$$

As mentioned at the beginning of this section, the slope of the line represented sensitivity when the relationship was linear. The slope of this line was m = 630,374. This indicates that, on the one hand, there was a direct (positive slope) relationship. On the other hand, and in numerical terms, we observed that births increased by 630 people, when the nuclear power rate increased one thousandth.

(Please insert Figure 16 about here)

The relationships between deaths and the energy variables are summarised in Table 4. The analysis performed and the conclusions drawn were similar to Births.

(Please insert Table 4 about here)

Finally, Table 5 shows the relationships between the *HDI* and the energy variables.

(Please insert Table 5 about here)

To summarise, after studying the direct relationships observed in the data simulated among the energy variables and births, deaths and the *HDI*, we state that in general:

- In Births, Deaths and the *HDI*, a direct relationship was observed with the three energy variables (renewable energies, oil and nuclear power), and also with forest area, but not with coal and gas.
- Births rose when oil and nuclear power consumption increased, but they lowered when the consumption of renewable energies and forest area increased.
- What occurred with births also took place with deaths.
- In contrast, the *HDI* rose when renewable energies and forest area did, but decreased with increasing oil and nuclear power consumption.
- An increase in Births/Deaths was associated with a rise in *EQUI*, *CONE* and *CO2E*.
- In contrast, the *HDI* decreased when *EQUI*, *CONE* and *CO2E* increased.

6. Conclusions

This paper presents an index that attempts to measure environmental quality from the variables related with energy consumption and CO_2 emissions. It is a geometric mean that involves three variables: CO_2 emissions, nuclear power and renewable energies. The values of this index range between 0 and 1, with 0 being the optimal value; i.e., the closer we come to a value of 0, renewable energies increase, while nuclear power and CO_2 emissions diminish.

This index has been introduced into a gender-defined demographic model (including three of the well-being variables defined by the United Nations: *HDI*, *GDI*, *GEM*) through birth and death rates. The new formulae for these rates have been validated for Spain for the 2001-2010 period, and higher determination coefficients were obtained than in previous related papers. The new extended model has been validated in terms of its deterministic and stochastic formulation through the Spanish male and female populations during the 2001-2010 period.

An application of this new model is proposed. It consists in a sensitivity analysis based on Spain's previous situation (2001-2010) which uses simulated data for the next decade (2011-2020). Note that the more relevant environment-related input variables used to control births, deaths and the *HDI* are: use of renewable energies, nuclear power, oil and existing forest area. We wish to stress that this solution is specific for Spain's situation today, despite the fact that the general model formulation allows the same analysis to be done for other countries when their historical data are employed.

Future work is expected to obtain the information required to apply such an analysis to other countries. This new information will help us, if necessary, to also fine tune the design of the environmental quality index presented herein.

As regards the evolution of the global model that served as a basis, we believe that the demographic part of the model should include age cohorts in the future to, for example, calculate life expectancy at birth from deaths and population in order to note how this variable varies according to the environmental variables.

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Variable	Minimum	Maximum
CO_2 emissions (Mtc)	0.01025852	101.954214
Coal (Ktep)	4000	25000
Oil (Ktep)	6000	75000
Natural Gas (Ktep)	9000	40000
Forest Area (Ha)	10000000	40000000

Table 1. Variables used to calculate CO_2 emissions, with their maximum and minimum values, to normalise real data. Mtc=metric tons per capita, Ktep= thousand tons of equivalent oil. Ha=hectares.

Variable	Minimum	Maximum
CO_2 emissions (Mtc)	0.01025852	101.954214
Nuclear power (Ktep)	9000	20000
Renewable energies (Ktep)	3000	17000

Table 2. Variables used to calculate *EQUI*, with their maximum and minimum values to normalise real data. Mtc=metric tons per capita, Ktep= thousand tons of equivalent oil. Ha=hectares.

Variable	Fitted Function	R^2
REEN	$Births=-1.69567\cdot10^7+4.02469\cdot10^7\cdot reen-0.3185\cdot10^7\cdot reen^2$	0.915209
PETR	$Births=360458+509688\cdot petr-478264\cdot petr^2$	0.978178
NUCL	$Births = 265642 +630374\cdot nucl$	0.99479
FOSU	$Births=6.99712\cdot10^7-1.17457\cdot10^8\cdot fosu$	0.993239
EQUI	$Births= -2254.96+4.20247\cdot10^6\cdot equi-7.78129\cdot10^6\cdot equi^2$	0.988539
CONE	$Births=-1.03817\cdot10^7 +173.732\cdot cone-0.000692913\cdot cone^2$	0.992624
CO2E	$Births=-1.1718\cdot10^6 +6.64262\cdot10^7\cdot co2e-6.56331\cdot10^8\cdot co2e^2$	0.987838

Table 3. Relationships between births and the energy variables.

Variable	Fitted Function	R^2
REEN	$Deaths = -4.47599\cdot10^6+1.11967\cdot10^7\cdot reen-6.43738\cdot10^6\cdot reen^2$	0.85187
PETR	$Deaths = 352358 +148273\cdot petr-150122\cdot petr^2$	0.940898
NUCL	$Deaths = 326963 +171859\cdot nucl$	0.994368
FOSU	$Deaths = 1.92475\cdot10^7-3.18816\cdot10^7\cdot fosu$	0.984114
EQUI	$Deaths = 234270+1.43884\cdot10^6\cdot equi-3.17256\cdot10^6\cdot equi^2$	0.996328
CONE	$Deaths=-2.66918\cdot10^6+49.0826\cdot cone-0.000196754\cdot cone^2$	0.978276
CO2E	$Deaths = -62023.2 +1.81067\cdot10^7\cdot co2e-1.80379\cdot10^8\cdot co2e^2$	0.96625

Table 4. Relationships between deaths and the energy variables.

Variable	Fitted Function	R^2
REEN	$HDI = 3.48012 - 5.86834 \cdot reen + 3.33633 \cdot reen^2$	0.7619
PETR	$HDI = 0.916125 - 0.074374 \cdot petr + 0.0923047 \cdot petr^2$	0.903823
NUCL	$HDI = 0.946633 - 0.244185 \cdot nucl + 0.340663 \cdot nucl^2$	0.991066
FOSU	$HDI = 4754.51 - 16070.8 \cdot fosu + 13583 \cdot fosu^2$	0.996103
EQUI	$HDI = 0.986776 - 0.909672 \cdot equi + 32.46424 \cdot equi^2$	0.989948
CONE	$HDI = 2.54239 - 0.000026822 \cdot cone + 1.09647 \cdot 10^{-10} \cdot cone^2$	0.974054
CO2E	$HDI = 1.12462 - 9.30345 \cdot co2e + 97.1069 \cdot co2e^2$	0.958057

Table 5. Relationships between the *HDI* and the energy variables.

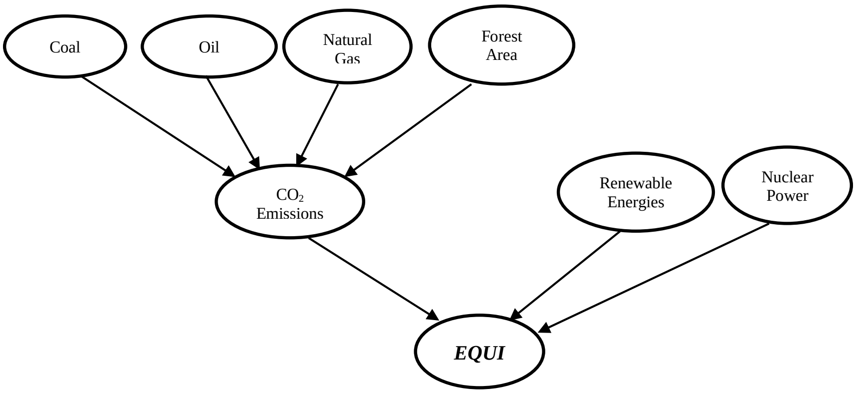


Figure 1. The variables involved in the Environmental Quality Index, *EQUI*.

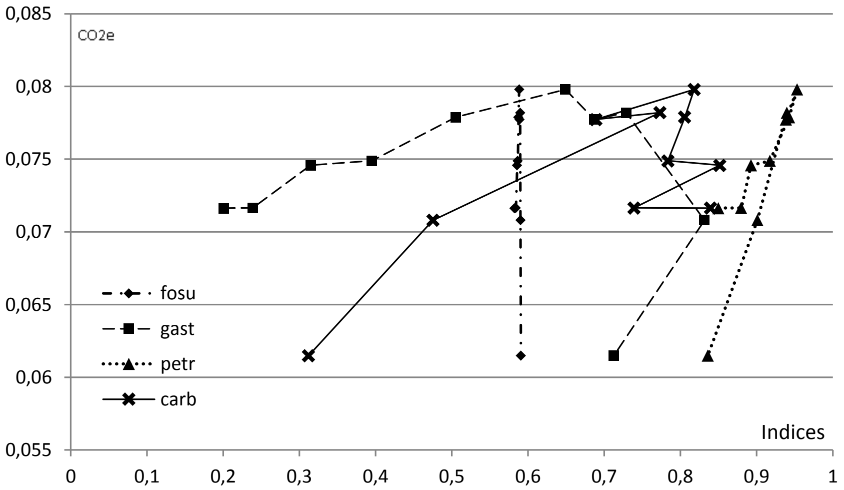


Figure 2. CO_2 emissions (metric tons per capita) versus the indices of coal consumption (carb), natural gas consumption (gast), forest area (fosu), oil consumption (petr). Spain, 2000-2009.

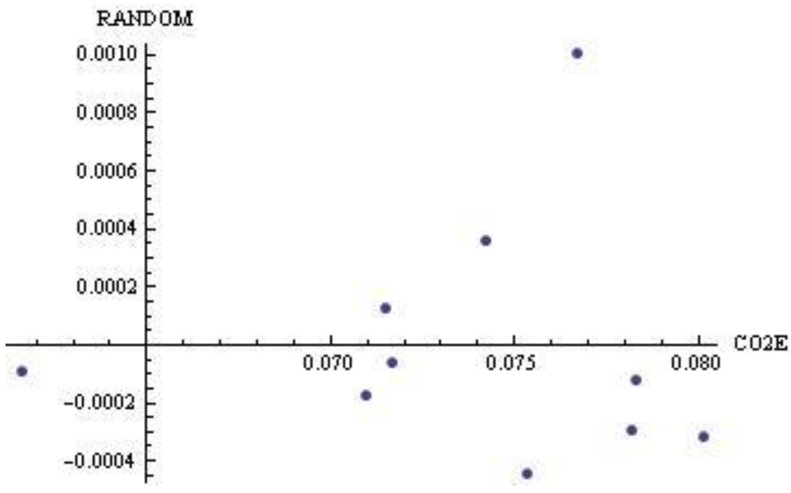


Figure 3. Random remainder of Equation (2) versus real CO_2 emissions (metric tons per capita). Spain, 2000-2009. $R^2 = 0.993819$. Kolmogorov-Smirnov Test: 0.254951.

$$rdef = 4.74874 - \frac{5}{1 + e^{-3.59069\,(-1.76+x)}} + \frac{8.52895}{1 + e^{-2.1185\,(-1.33555+x)}}$$

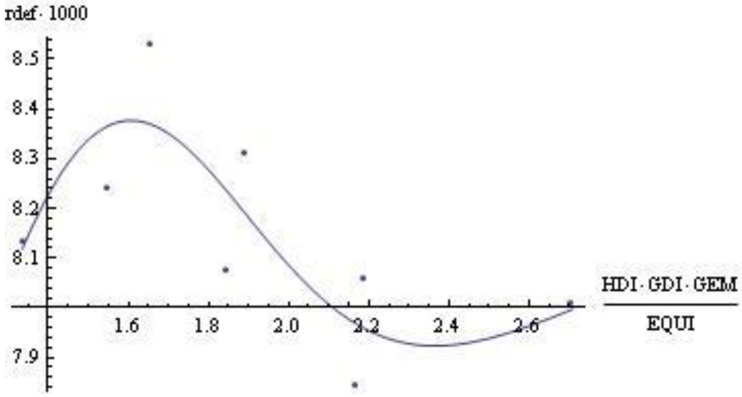


Figure 4. Fitting the Female Death Rate (*rdef*) in relation to the quality variables. Real data (dots), simulated data (line). Spain, 2001-2010. $R^2 = 0.650736$.

$$rdem = -1.09555 + \frac{12}{1 + e^{-0.243686\,(-1.5+x)}} + \frac{9.50337}{1 + e^{0.591043\,(-1.33+x)}}$$

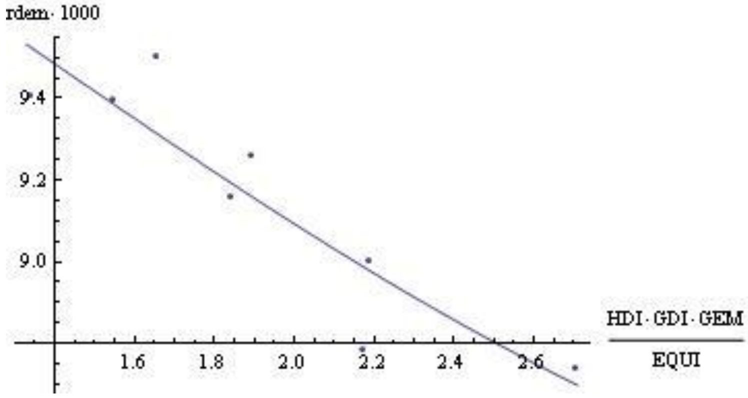


Figure 5. Fitting the Male Death Rate (*rdem*) in relation to the quality variables. Real data (dots), simulated data (line). Spain, 2001-2010. $R^2 = 0.82117$.

$$rfef = \quad 8.15695 + \frac{100}{1+e^{-2.58141\,(-1.5+x)}} + \frac{94}{1+e^{2.3812\,(-1.33+x)}}$$

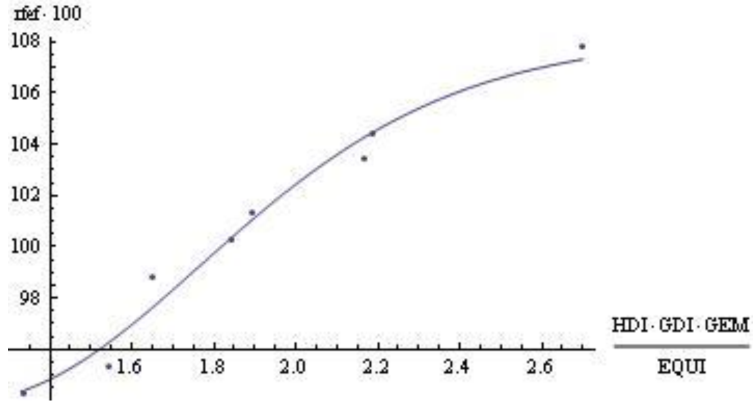


Figure 6. Fitting the Female Birth Rate (*rfef*) in relation to the quality variables. Real data (dots), simulated data (line). Spain, 2001-2010. $R^2 = 0.976886$.

$$rfem = 5.42031 + \frac{110}{1 + e^{-2.31109\,(-1.5+x)}} + \frac{100}{1 + e^{2.06817\,(-1.33+x)}}$$

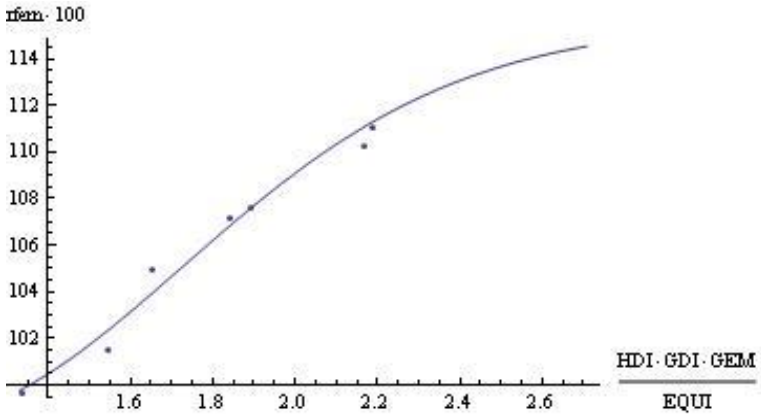


Figure 7. Fitting the Male Birth Rate (*rfem*) in relation to the quality variables. Real data (dots), simulated data (line). Spain, 2001-2010. $R^2 = 0.983279$.

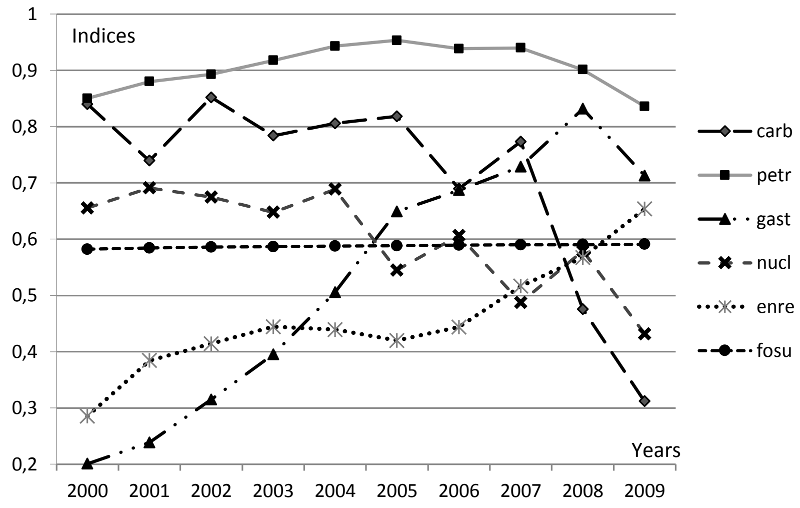


Figure 8. Indices of: Coal consumption (carb), Renewable energies consumption (enre), Natural gas consumption (gast), Nuclear power consumption (nucl), Forest area (fosu), Oil consumption (petr), all of them versus time. Spain, 2000-2009.

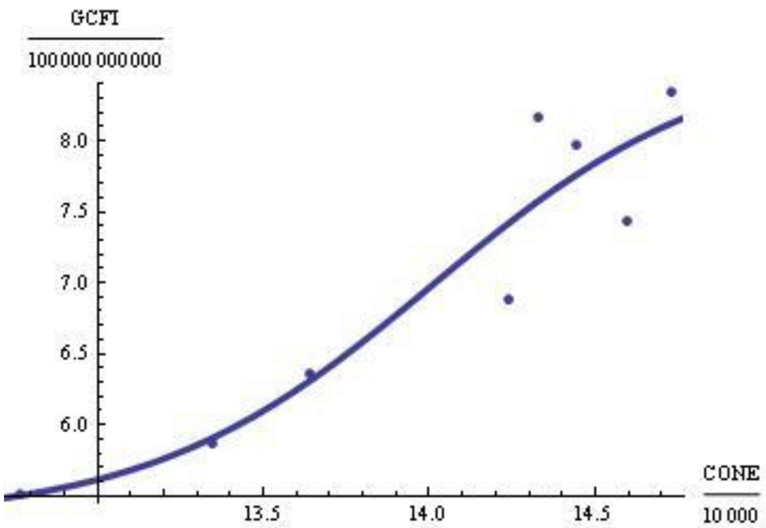


Figure 9. Fitting the final consumption expenditure (*GCFI*) in relation to energy consumption (*CONE)*. Spain, during the 2000-2009 period. R^2 = 0.911381. Kolomogorov-Smirnov test: 0.1333.

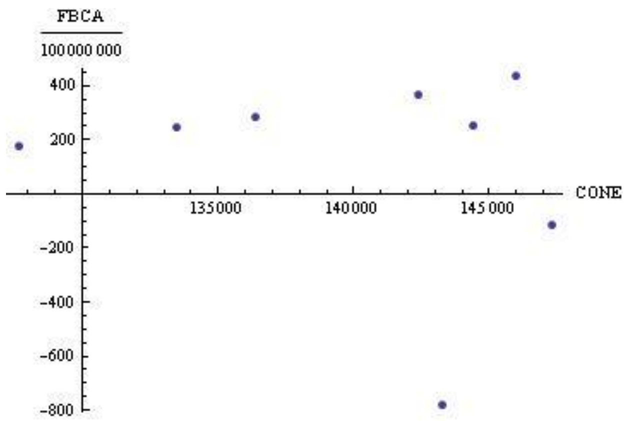


Figure 10. Gross capital formation (*FBCA*) versus energy consumption (*CONE)*. Spain, 2000-2009.

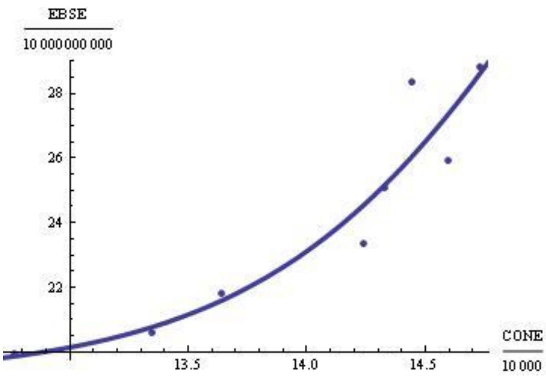


Figure 11. Fitting Exports of goods and services (*EBSE*) in relation to energy consumption (*CONE*). Spain, during the 2000-2009 period. R^2=0.888753. Kolomogorov-Smirnov test, 0.233744.

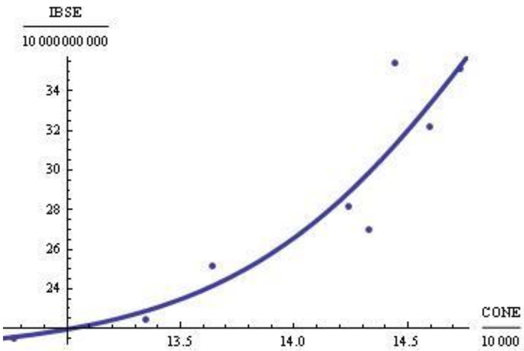


Figure 12. Fitting Imports of goods and services (*IBSE*) in relation to energy consumption (*CONE*). Spain, during the 2000-2009 period. R^2=0.861259. Kolomogorov-Smirnov test, 0.261592.

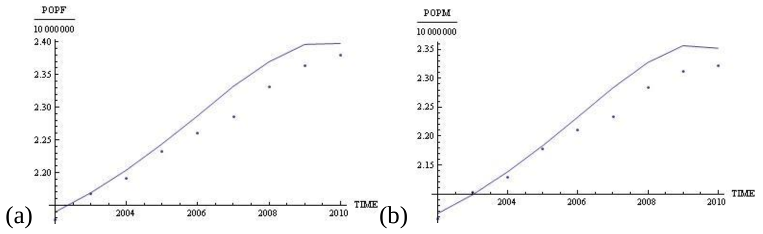
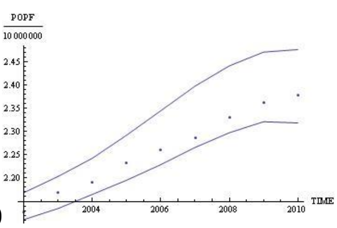


Figure 13. The forecast function (solid line) given by the model and real data (dots) for: (a) Spanish Female Population (*POPF*) and (b) Spanish Male Population (*POPM*), both during the 2001-2010 period. In (a) R^2=0.990853, with a maximum relative error of 1.92638%. In (b) R^2=0.991516, with a maximum relative error of 2.211898%.

(a) 

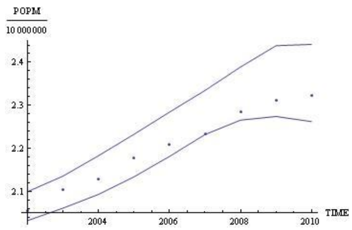
(b) 

Figure 14. (a) Spanish Female Population 2001-2010. (b) Spanish Male Population 2001-2010. Minimum and Maximum values (solid lines) and real values (dots).

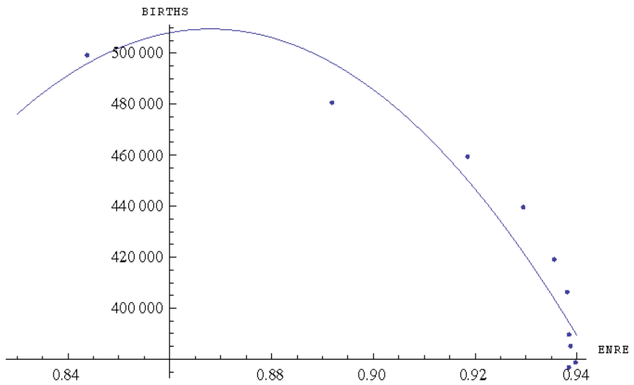


Figure 15. Births and renewable energies (*ENRE*). Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period. R^2=0.915209.

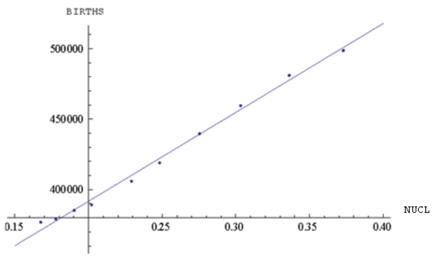
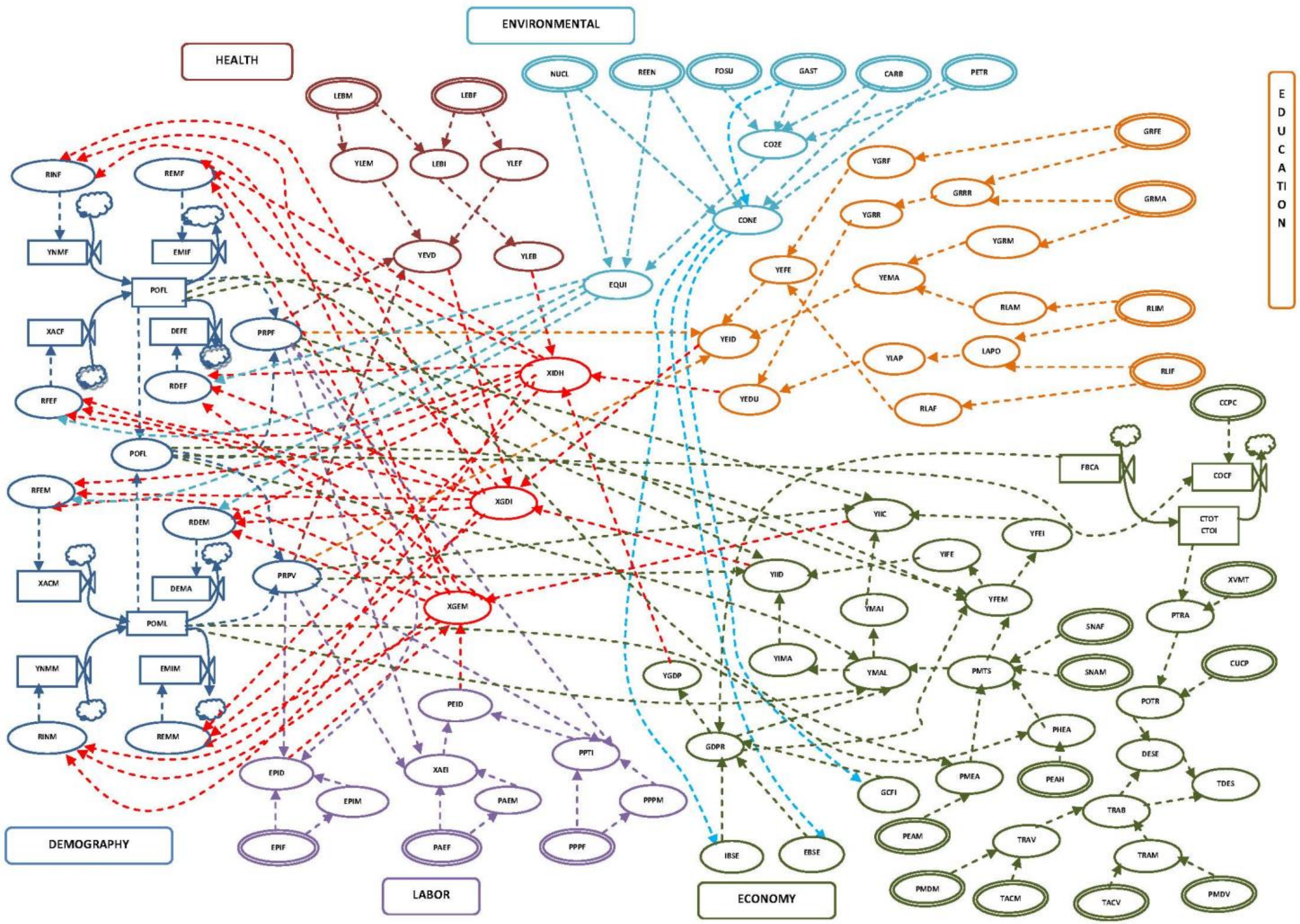


Figure 16. Births versus nuclear power (*NUCL*). Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period. R^2=0.99479.

Appendix 1

The model: variables and their mutual influences.

(This appendix may be situated on a web page)



Con formato: Fuente: (Predeterminada) +Cuerpo (Calibri)

Figure 1. Forrester diagram of the model.

Let's recall that Forrester diagrams are hydrodynamic similes in which variables are usually classified as follows:

- Level variables: they require an initial value, which is an input variable, and the following values are updated. They are represented by a square or rectangle, and can be compared to the tanks in which fluid is stored.
- Flow variables: they can be compared with the stopcocks that regulate flow to or from a fluid tank. They are represented by a distinctive icon that resembles a stopcock.
- Auxiliary variables: these are either the intermediate variables used to calculate flows or are strict output variables (not used in other calculations, but are usually the variables to be optimised). They are represented by a circle or an ellipse.
- Input variables: they are not calculated in the model, and are classified into:
  • Scenario variables: input variables that are not controlled.
  • Control variables: input variables whose value can be assigned by the person using the model.
  • Constants: system parameters with a known and fixed value.

All the input variables are represented by a doubled-line circle or ellipse. Sources or sinks (the origin or destination of flows) are represented by a cloud.

MODEL's VARIABLES

DEMOGRAPHY

```
DEFE Female Deaths [population] (flow variable)
DEMA Male Deaths [population] (flow variable)
DETO Total Deaths [population] (auxiliary variable)
EMIF Female Emigration [population] (flow variable)
EMIG Total Emigration [population] (auxiliary variable)
EMIM Male Emigration [population] (flow variable)
POFI Female Population at the beginning of the year [population]
       (constant)
POFL Female Population at the end of the year [population] (level
       variable)
POMI Male Population at the beginning of the year [population]
       (constant)
POML Male Population at the end of the year [population] (level
       variable)
POPI Population at the beginning of the year [population] (auxiliary
       variable)
POPL Population at the end of the year [population] (auxiliary
       variable)
PRPF Female proportion (auxiliary variable)
PRPM Male proportion (auxiliary variable)
RDEF Female Death Rate [%] (auxiliary variable)
RDEM Male Death Rate [%] (auxiliary variable)
REMF Female emigration rate [%] (auxiliary variable)
REMM Male emigration rate [%] (auxiliary variable)
RFEF Female Birth rate [births/female population] (auxiliary variable)
RFEM Male Birth rate [births/female population] (auxiliary variable)
```

RINF Female immigration rate [%] (auxiliary variable)
RINM Male immigration rate [%] (auxiliary variable)
TEMI Initial year [time] (constant)
TEMS Year [time] (level variable)
XACF Female Births [population] (flow variable)
XACI Total Births [population] (auxiliary variable)
XACM Male Births [population] (flow variable)
YNMF Female immigration [population] (flow variable)
YNMI Total immigration [population] (auxiliary variable)
YNMM Male immigration [population] (flow variable)

EDUCATION
GRFE Female Gross Registered to level primary, secondary and tertiary [%] (setting variable)
GRMA Male Gross Registered to level primary, secondary and tertiary [%] (setting variable)
GRRR Gross Rate Registered to level primary secondary and tertiary [%] (auxiliary variable)
LAPO Literate Adult Population [%] (auxiliary variable)
RLAF Female literacy rate adults [%] (auxiliary variable)
RLAM Male literacy rate adults [%] (auxiliary variable)
RLIF Female literacy rate [%] (setting variable)
RLIM Male literacy rate [%] (setting variable)
YEDU Educational Index [%] (auxiliary variable)
YEID Equally Distributed Education Index [%] (auxiliary variable)
YEFE Female Education Index [%] (auxiliary variable)
YEMA Male Education Index [%] (auxiliary variable)
YGRF Female Gross Rate Registered to level primary secondary and tertiary [%] (auxiliary variable)
YGRM Male Gross Rate Registered to level primary secondary and tertiary [%] (auxiliary variable)
YGRR Gross Rate Registered to level primary secondary and tertiary index [%] (auxiliary variable)
YLAP Literacy Rate Adults [%] (auxiliary variable)

LABOR
EPID Percentage parliamentary representation [%] (auxiliary variable)
EPIF Female Percentage parliamentary representation [%] (setting variable)
EPIM Male Percentage parliamentary representation [%] (auxiliary variable)
PAEF Female percentage shares of positions as legislators senior officials and managers [%] (setting variable)
PAEM Male percentage shares of positions as legislators senior officials and managers [%] (auxiliary variable)
PEID Average PEID [%] (auxiliary variable)
PPPF Female percentage shares of professional and technical positions [%](setting variable)
PPPM Male percentage shares of professional and technical positions [%](auxiliary variable)
PPTE PEID [%] (auxiliary variable)
PPTI Professional index [%] (auxiliary variable)
XAEE PEID within index [%] (auxiliary variable)
XAEI PEID index senior [%] (auxiliary variable)

HEALTH
LEBF Female life expectancy at birth [age] (setting variable)
LEBI Life expectancy at birth [age] (auxiliary variable)
LEBM Male life expectancy at birth [age] (setting variable)
YEVD Equally Distributed life expectancy at birth index [%] (auxiliary variable)

YLEB Life expectancy at birth index [%] (auxiliary variable)
YLEF Female life expectancy at birth index [%] (auxiliary variable)
YLEM Male life expectancy at birth index [%] (auxiliary variable)

ECONOMY
CCPC Consumption of fixed capital per capita [€](setting variable)
COCF Consumption of fixed capital [€] (auxiliary variable)
CTOI Initial total fixed capital [€] (setting variable)
CTOT Total fixed capital [€] (auxiliary variable)
CUCP Coefficient of utilization of productive capacity [proportion] (setting variable)
EBSE Welfare and services exports [€] (setting variable)
DESE Number of unemployed people [population] (auxiliary variable)
FBCA Gross capital formation [€] (setting variable)
GCFI Final consumption expenditure [€] (setting variable)
GDPR Gross Domestic Product [PPP US$] (auxiliary variable)
IBSE Welfare and services imports [€] (setting variable)
PEAH Economically active male population [population] (setting variable)
PEAM Economically active female population [population] (setting variable)
PHEA Economically active male percentage [%] (auxiliary variable)
PMDM Female population at working age [population] (setting variable)
PMDV Male population at working age [population] (setting variable)
PMEA Economically active female percentage [%] (auxiliary variable)
PMTS Proportion of women in total wages [%] (auxiliary variable)
POTR Population working [population] (auxiliary variable)
PTRA Number of jobs [] (auxiliary variable)
SNAF Female non-agricultural wage [€] (setting variable)
SNAM Male non-agricultural wage [€] (setting variable)
TACM Female labor force rate [proportion] (setting variable)
TACV Male labor force rate [proportion] (setting variable)
TDES Unemployment rate [%] (auxiliary variable)
TRAB Economically active population [population] (auxiliary variable)
TRAM Female workers [population] (auxiliary variable)
TRAV Male workers [population] (auxiliary variable)
XVMT Average value of a new job place [€] (setting variable)
YFEI Female income [PPP US$] (auxiliary variable)
YFEM Female income [PPP US$] (auxiliary variable)
YGDP Gross Domestic Product Index [%] (auxiliary variable)
YIIC Total income [PPP US$] (auxiliary variable)
YIID Equally Distributed Income Index [%] (auxiliary variable)
YIFE Female income index [%] (auxiliary variable)
YIMA Male income index [%] (auxiliary variable)
YMAI Male Income [PPP US$] (auxiliary variable)
YMAL Male income [PPP US$] (setting variable)

ENVIRONMENTAL
CARB Coal [ktep] (setting variable)
CONE Addition of all energies [ktep] (auxiliary variable)
CO2E CO_2 emissions [ktep] (auxiliary variable)
FOSU Forest area [ha](setting variable)
GAST Natural gas [ktep] (setting variable)
NUCL Nuclear power [ktep] (setting variable)
PETR Oil [ktep] (setting variable)
REEN Renewable energies [ktep] (setting variable)

WELFARE VARIABLES
EQUI Environmental Quality Index [%] (auxiliary variable)
XDII Human development Index initial value [%] (constant)
XHDI Human development Index [%] (level variable)

```
XGDI Gender Development Index [%] (level variable)
XGII Gender Development Index initial value [%] (constant)
XGEM Gender Empowerment Index [%] (level variable)
XIPI Gender Empowerment Index initial value [%] (constant)
```

Appendix 2

Details of the study

(This appendix may be placed on a web page)

1. Births

Figure 1 and Table 1 show the functions fitted to the direct relationship between births and the corresponding energy consumption variable. The different input variables are on the x-axis and births lie on the y-axis, all of which correspond to the simulated 2011-2020 period. At the bottom of each figure, we include the function that fits the simulated data to help draw conclusions from these relationships.

With variables *GAST* and *CARB*, no direct relations were found. Therefore, we neither provided graphs nor analysed these cases.

Variable	Fitted Function	R^2
REEN	$Births=-1.69567\cdot10^7+4.02469\cdot10^7\cdot reen-0.3185\cdot10^7\cdot reen^2$	0.915209
PETR	$Births=360458+509688\cdot petr-478264\cdot petr^2$	0.978178
NUCL	$Births=265642+630374\cdot nucl$	0.99479
FOSU	$Births=6.99712\cdot10^7-1.17457\cdot10^8\cdot fosu$	0.993239

Table 1. Relation between births and the energy variables.

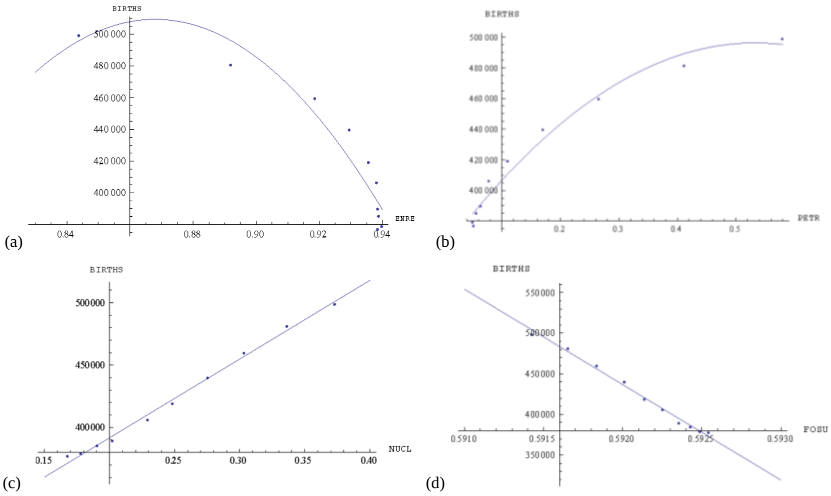


Figure 1. Births versus: (a) renewable energies, (b) oil, (c) nuclear power, (d) forest area. Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.

When interpreting these results (Table 1), we see that renewable energies are clearly related with births ($R^2 = 0.91$). The parabola resulting from the fit to the simulated data can be interpreted as follows (note that in all cases, the environment-related variables were normalised, so they took values of between 0 and 1):

1 - The potential impact associated with a possible variation in *REEN* was calculated using derivative function $2\,(-2.3185\cdot10^7)\,reen + 4.02469\cdot10^7$.
2 - The maximum value of simulated births (roughly 300,000 people) was associated with a renewable energies value, $REEN = -4.02469\cdot10^7/\,(2\,(-2.3185\cdot10^7)) = 0.868$.
3 - As the simulated *REEN* values between 2011-2020 were between 0.84 and 0.94, an increase of one-thousandth in their lowest value was associated with variation in Births: $(2\,(-2.3185\cdot10^7)\,0.84 + 4.02469\cdot10^7)\,0.001 = 1296$, while the same increase in their higher value was associated with variation in Births: $(2\,(-2.3185\cdot10^7)\,0.94 + 4.02469\cdot10^7)\,0.001 = -3341$; that is, sensitivity of Births in relation to Renewable Energies would be great, and would be positive near the lower limit, negative near the upper limit, and very low near the value of 0.868.
4 - . Using the same procedure, any intermediate value can be obtained.

By changing the data, this can be carried out with oil in the same manner (Figure 1b).

Conversely, for the case of nuclear power and forest area, the relationship was linear. As mentioned at the beginning of this section, the slope of the line represented sensitivity when the relationship was linear. For example, if we look at the graph corresponding to nuclear power (Figure 1c), the slope of this line is m = 630,374. This indicates that there was a direct (positive slope) relationship; in numerical terms, for every one thousandth that the nuclear power rate increased, we observe that births increased by 630 people.

Figure 2 and Table 2 show the functions fitted to the direct relationship between births and *EQUI*, *CONE* and *CO2E*, respectively. The different input variables are on the x-axis and births lie on the y-axis, all of which correspond to the simulated period covering 2011-2020. At the bottom of each figure, we include the function that fits the simulated data to help draw conclusions from these relationships.

Variable	Fitted Function	R^2
EQUI	$Births= -2254.96+4.20247\cdot10^6\cdot equi-7.78129\cdot10^6\cdot equi^2$	0.988539
CONE	$Births =-1.03817\cdot10^7 +173.732\cdot cone-0.000692913\cdot cone^2$	0.992624
CO2E	$Births =-1.1718\cdot10^6 +6.64262\cdot10^7\cdot co2e-6.56331\cdot10^8\cdot co2e^2$	0.987838

Table 2. Relation between births and *EQUI*, *CONE* and *CO2E*.

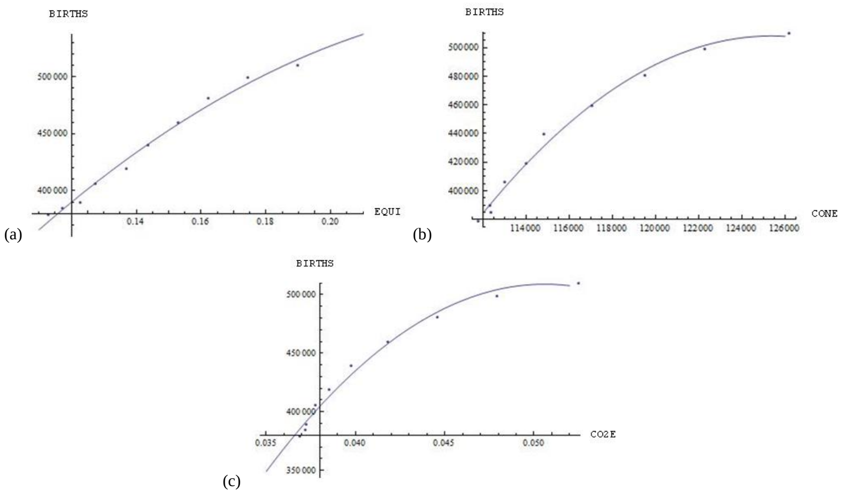


Figure 2. Births versus: (a) *EQUI*, (b) *CONE*, (c) *CO2E*.
Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.

When interpreting these results (Table 2), *EQUI* is clearly related with births ($R^2 = 0.988$). The parabola resulting from the fit to the simulated data can be interpreted as follows:

1 - The potential impact associated with a possible variation in *EQUI* was calculated using derivative function $2\ (-7.78129\cdot10^6)\ equi + 4.20247\cdot10^6$.
2 - The maximum value of simulated births (roughly 560000 people) was associated with an *EQUI* value of: $EQUI = -4.20247\cdot10^6 / (2\ (-7.78129\cdot10^6)) = 0.27$.
3 - As the simulated *EQUI* values between 2011-2020 were between 0.11 and 0.19, an increase of one-thousandth in their lowest value was associated with variation in Births of: $(2\ (-7.78129\cdot10^6)\ 0.11 + 4.20247\cdot10^6)\ 0.001 = 2490$, while the same increase in their highest value was associated with variation in Births of: $(2\ (-7.78129\cdot10^6)\ 0.19 + + 4.20247\cdot10^6)\ 0.001 = 1245$; that is, the sensitivity of Births in relation to *EQUI* would be great, and would be positive near the lower limit, negative near the upper limit, and very low near the value of 0.27.
4 - . Using the same procedure, any intermediate value can be obtained.

By changing the data, this can be carried out with *CONE* and *CO2E* in the same manner.

2. Deaths

Figure 3 and Table 3 depict the relationship between deaths and the various input variables, all of which correspond to the simulated 2011-2020 period. At the bottom of each figure, the function that fits the data is included. Once again, no direct relationship between deaths and variables *CARB* and *GAST* was found.

Variable	Fitted Function	R^2
REEN	$Deaths = -4.47599\cdot10^6+1.11967\cdot10^7\cdot reen-6.43738\cdot10^6\cdot reen^2$	0.85187
PETR	$Deaths = 352358 +148273\cdot petr-150122\cdot petr^2$	0.940898
NUCL	$Deaths = 326963 +171859\cdot nucl$	0.994368
FOSU	$Deaths = 1.92475\cdot10^7-3.18816\cdot10^7\cdot fosu$	0.984114

Table 3. Relationships between deaths and the energy variables.

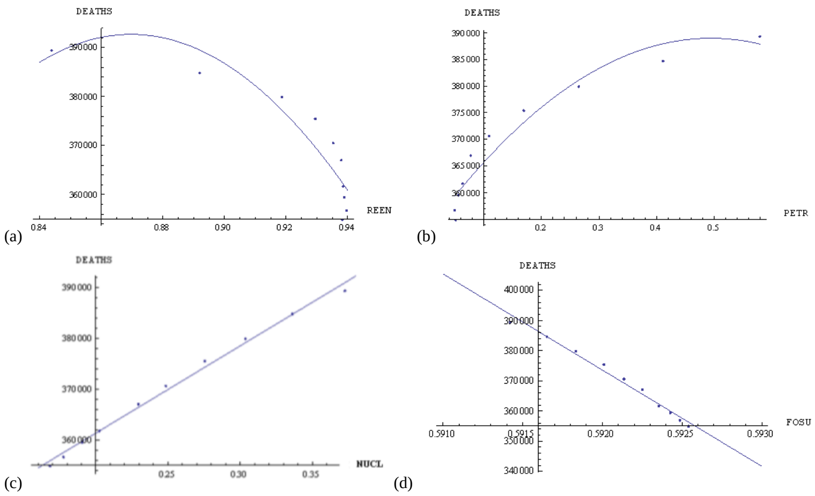


Figure 3. Deaths versus: (a) renewable energies, (b) oil, (c) nuclear power, (d) forest area. Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.

The analysis performed and the conclusions drawn were similar to Births.

Figure 4 and Table 4 depict the relationship between deaths and *EQUI*, *CONE* and *CO2E*, all of which correspond to the simulated 2011-2020 period. At the bottom of each figure, the function that fits the data is included.

Variable	Fitted Function	R^2
EQUI	$Deaths = 234270+1.43884 \cdot 10^6 \cdot equi-3.17256 \cdot 10^6 \cdot equi^2$	0.996328
CONE	$Deaths=-2.66918 \cdot 10^6+49.0826 \cdot cone-0.000196754 \cdot cone^2$	0.978276
CO2E	$Deaths = -62023.2 +1.81067 \cdot 10^7 \cdot co2e-1.80379 \cdot 10^8 \cdot co2e^2$	0.96625

Table 4. Relationships between deaths and *EQUI*, *CONE* and *CO2E*.

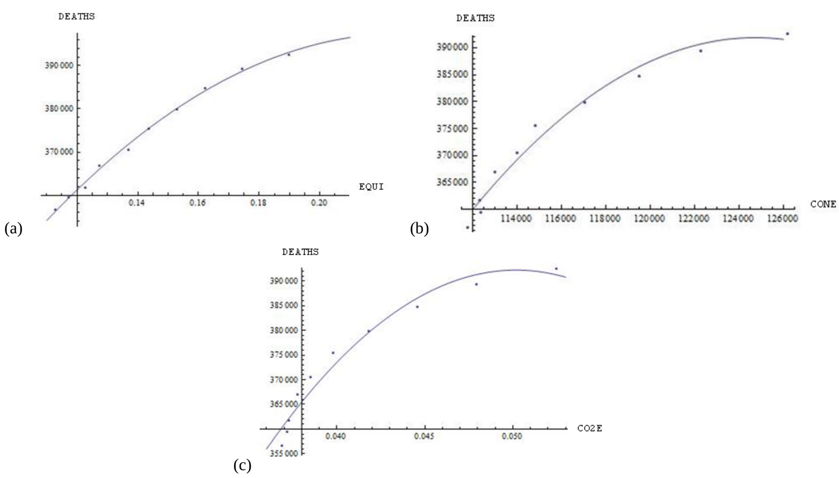


Figure 4. Deaths and (a) *EQUI*, (b) *CONE*, (c) *CO2E*.
Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.

The analysis performed and the conclusions drawn were similar to Births.

3. **Human Development Index, *HDI***

Figure 5 and Table 5 illustrate the relationship observed between the *HDI* and the various input variables, all of which correspond to the simulated 2011-2020 period. At the bottom of each figure, the function that fits the data is included. Once again, no direct relationship between *HDI* and variables *GAST* and *CARB* was found.

Variable	Fitted Function	R^2
REEN	$HDI = 3.48012 - 5.86834 \cdot reen + 3.33633 \cdot reen^2$	0.7619
PETR	$HDI = 0.916125 - 0.074374 \cdot petr + 0.0923047 \cdot petr^2$	0.903823
NUCL	$HDI = 0.946633 - 0.244185 \cdot nucl + 0.340663 \cdot nucl^2$	0.991066
FOSU	$HDI = 4754.51 - 16070.8 \cdot fosu + 13583 \cdot fosu^2$	0.996103

Table 5. Relationships between the *HDI* and the energy variables.

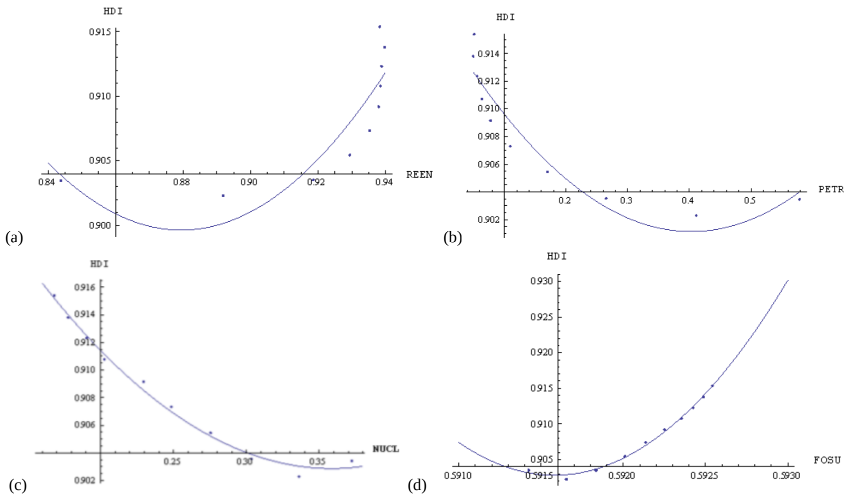


Figure 5. The *HDI* and (a) renewable energies, (b) oil, (c) nuclear power, (d) forest area. Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.

For the *HDI*, all the relationships were of a parabola type, and the detailed analysis can be done as in previous cases.

Figure 6 and Table 6 illustrate the relationship observed between the *HDI* and the *EQUI*, *CONE* and *CO2E*, all of which correspond to the simulated 2011-2020 period. At the bottom of each figure, the function that fits the data is included.

Variable	Fitted Function	R^2
EQUI	$HDI = 0.986776 - 0.909672 \cdot equi + 32.46424 \cdot equi^2$	0.989948
CONE	$HDI = 2.54239 - 0.000026822 \cdot cone + 1.09647 \cdot 10^{-10} \cdot cone^2$	0.974054
CO2E	$HDI = 1.12462 - 9.30345 \cdot co2e + 97.1069 \cdot co2e^2$	0.958057

Table 6. Relationships between the *HDI* and *EQUI*, *CONE* and *CO2E*.

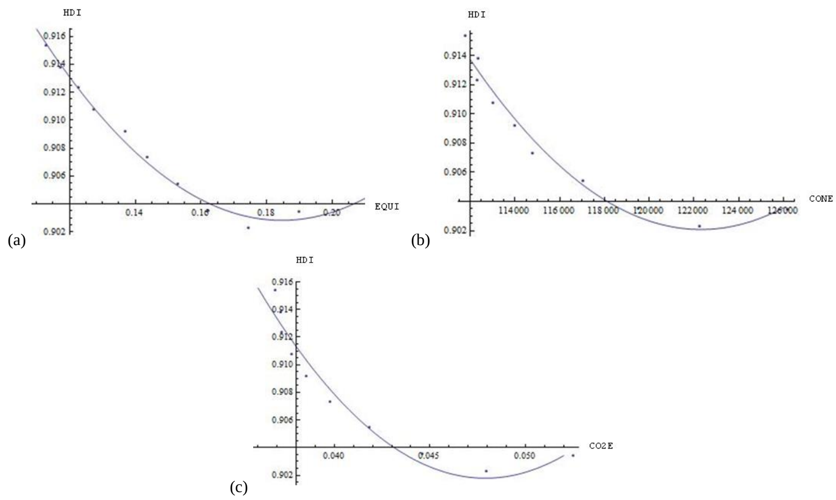


Figure 6. The *HDI* versus: (a) *EQUI*, (b) *CONE*, (c) *CO2E*. Simulated data (dots), fitted function (line). Spain, during the 2011-2020 period.