Modelling biodiversity

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Abstract

This study uses a sample of 71 countries and nonparametric quantile and partial regressions to model a number of threatened species (reptiles, mammals, fish, birds, trees, plants) in relation to various economic and environmental variables (GDPc, CO_2 emissions, agricultural production, energy intensity, protected areas, population and income inequality). From the analysis and due to high asymmetric distribution of the dependent variables it seems that a linear regression is not adequate and cannot capture properly the dimension of the threatened species. We find that using OLS instead of non-parametric techniques over- or under-estimates the parameters which may have serious policy implications.

Keywords: Nonparametric quantile regression; partial regression; biodiversity.

JEL Classifications: Q57, Q20, C14, C40

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1. Introduction

The biological diversity (biodiversity) is a concept entailed in the modern scientific and political terminology and in daily life with various social and economic dimensions. After the signing of the Convention on Biological Diversity (CBD) by a considerable number of countries (168 signatures in the 191 parties to the CBD)[1] in Rio de Janeiro in 1992, the term was recognized globally. Although there is no common definition accepted, the term biodiversity encompasses everything from the level of genes to species to the level of ecosystems. To be more specific, we may distinguish four level of biodiversity in genes, species, ecosystems and functional diversity (Turner et al. 1999).

Biodiversity and ecosystems provide us with a number of direct and indirect social and economic benefits. The significance of biodiversity lies in its role to preserve ecosystem resilience by guaranteeing the provision of basic ecosystem functions under a variety of environmental situations (Perrings *et al*. 1995, p. 4). The preservation of biodiversity is crucial due to the services provided by its use. These services may be aesthetic and ecological as they are related to the normal operation and conservation of ecosystems. They are also related to the reduction of poverty globally as well as to medical and pharmaceutical curative methods that rely on biological substances offered by the environment. Costanza et al. (2007) showed the complex relationships between biodiversity and ecosystem functioning. The latter supports ecosystem services that increase directly or indirectly human welfare.

Biodiversity is in danger due mainly to human activities. In the second half of the 20th century, human population was doubled from 2.5 billion in 1950 to more than 6 billion in 2000. At the same time the value of economic activity increased by more

[1] For more details see http://www.cbd.int/convention/parties/list/.

than 400% over the second half of last century (Delong, 2003). The area of natural habitat has been reduced for a number of reasons such as conversion of lands to agriculture, over-harvesting of fish, air and water pollution, climate change, urban development, increasing sequence of fires in forests, etc. For these reasons the current rates of species extinction have been dramatically increased.

Habitat loss and degradation may be considered as the main danger for biodiversity leading to the need of finding ways of preserving natural habitats. Governments could set biodiversity targets attempting to achieve them at minimum cost. This would still incorporate economic realities but avoid the (controversial) valuation of species. Alternatively governments may create protected areas like national parks where biodiversity may be protected. Globally it is estimated that 6.4% of the earth (with the exception of Greenland and Antarctica) is in some form of protected area (UNDP, 2000).

Threats to the natural habitat are in general lower in the developed countries compared to the tropical developing countries where much of the biodiversity resides. These threats vary according to the ecosystem type. Given the threat of extinction in a number of species and the limited capital budgets, the decision makers have to set priorities in order to make sure that conservation of biodiversity is ensured. Thus a complete and well-planned environmental policy requires the use of some form of economic valuation inevitable. The economic valuation of biodiversity consists of the effort to quantify in monetary terms the human preferences concerning the efforts to preserve the various species.

In this study a sample of 71 countries and a number of economic and environmental variables are used. Specifically, apart from variables like the gross domestic product per capita and the population that can be met as explanatory variables in other studies, a number of other variables are used for the first time like the CO_2 emissions per capita, agricultural production, energy intensity, protected areas in every country and the GINI index of income inequality. In the same way, variables like the number of species endangered are used for reptiles, mammals, fish, birds, trees and plants as dependent variables.

The results are interesting as we are not relying on simple statistical and econometric modelling methods like ordinary least squares (hereafter OLS), but we use, for the first time to our knowledge, quantile regression with reference not to the mean influence of the regressors on the mean of the conditional distribution of the dependent variable but on its entire conditional distribution. Quantile regressions rely on a number of different quantiles and estimate functional relationships between variables for all portions of a probability distribution. It is even more useful in cases with heterogeneous variances where OLS has serious problems (heteroskedastic error terms). In such cases focusing only on changes in the means may underestimate or overestimate or even fail to distinguish real nonzero changes in heterogeneous distributions (Terrell *et al.* 1996; Cade *et al.* 1999). At the same time using quantile regressions to model heterogeneous variances does not require any specification of how variances changes are related to the mean. Finally, in a specific case partial regression was used among the explanatory variables and not one but more than one dependent variables in the same model were simultaneously considered.

The structure of this study is the following. Section 2 reviews the problem in terms of exploring the research efforts carried out in evaluating economically biodiversity. Section 3 presents the data used, while section 4 discusses analytically the proposed econometric methodologies. Section 5 refers to the empirical results derived and the last section concludes the paper.

2. Literature review

Biodiversity comprises the variety of types, forms, spatial arrangement, interactions and processes from genes to species and ecosystems (Noss, 1990) together with the evolutionary history that led to their existence (Faith, 2002). Commonly used measures like the number of species present are fully scale-dependent and only show a change when species have disappeared. At the same time indices incorporating several proxy signals are quite sensitive while integrated measures (Scholes and Biggs 2005; Hui *et al.* 2008) are sensitive and achievable but they require more research in order to construct the globally robust relationships between population data, the variation in genetics and the required ecosystem conditions (Scholes *et al.* 2008). Genetically distinct populations are an important component of biodiversity for any species (Hughes et al. 1997).

One of the main concerns of the environmental social sciences is the deep understanding of the social and economic forces that change the environment. Scholars have contributed to global biodiversity loss research by paying attention to the relevance and context of species in threat to the interdisciplinary community (Hoffman, 2004; Naidoo and Adamowicz, 2001). Due to data limitations and reliability cross national comparisons have tackled basically the loss of land-based species like birds and mammals. The studies mentioned only partially capture the cumulative effects of human activity on global diversity. The proximate causes of losses in biodiversity are probably well understood in cases of habitat destruction, resource extraction, climate change and pollution.

But socioeconomic forces have poorly explored in biophysical phenomena. Mikkelson *et al.* (2007) using OLS tested how strongly economic inequality is related to biodiversity losses and found that among countries (and the USA) the number of threatened species increases significantly with the GINI ratio of inequalities in income. O'Connor et al. (2003) using a combination of biological and sociological variables (among others GDP/c, population density, percentage of unprotected land area and governance) in the context of a return on investment framework try to explore the establishment of conservation priorities. They find that only a few countries emerged as high priorities regardless of which factors were examined. On the other hand, some countries ranked highly as priorities for conservation when focusing solely on biological metrics, did not reach a high rank when governance, population pressure, economic costs and conservation needs were considered.

Nunes and van den Bergh (2001) present a literature review of the economic valuation of biodiversity according to the various available methods. Most of these studies have been carried out in the USA and show the existence of positive social value of biodiversity but they show simultaneously that the economic literature is incomplete and unable to cover the full range of benefits from biodiversity.

Brody (2003) using regression analysis examines how existing biodiversity levels affect ecosystem capabilities at the local level. On the other hand, Costanza et al. (2007) using stepwise regression (OLS) found that biodiversity and primary productivity are positively related in certain temperature regimes showing that a change in biodiversity is correlated with a change in net primary production. It is worth mentioning that the authors find nonlinear relationships for a number of predictors which were recalculated and transformed. Similarly, Groeneveld et al. (2005) present a spatially explicit trade-off analysis of species preservation in agricultural areas calculating the production possibility frontiers of net monetary benefits from agriculture and preservation of three species with different habitats.

In these lines, Clausen and York (2008) employ cross sectional data for different fish species in threat and in more than 140 countries. By using a negative binomial regression model test the environmental Kuznets curve hypothesis regarding both the scale of economic production and urbanization. Dietz and Adger (2003), with the use of panel and cross-sectional data, examined economic growth and biodiversity in the EKC framework. Specifically they investigate the relationship between economic growth, loss of biodiversity and policies to conserve biodiversity. The authors base their effort on the idea that if economic growth causes biodiversity loss by transforming habitat and other means, then an inverse relationship should be expected.

3. Data used

One of the most commonly used methods of describing biodiversity of an area is the count of species that reside in this area. Obviously a complete enumeration of all species even in a simple square metre is impossible, as the vast majority of species remains unknown. At the same time there are cases of existence of different definitions for species creating different estimates of their richness. Additional problems arise in the analysis of the geographical distribution of the various species, the change of these distributions in time etc. The huge variety of living creatures is ranked in multiple levels (from genes to ecosystems) making their complete enumeration extremely difficult and in many cases infeasible.

As mentioned in this study we use economic and environmental data. Specifically a number of variables are used as explanatory such as the Gross Domestic Product (GDP in million $) and the per capita Gross Domestic Product (GDPc), per capita CO_2 emissions (in tons CO_2 per million $), total agricultural production index

(1999-2001=100), energy intensity in all economics sectors (toe per million $), national protected areas (total number) in every country[2], population (in thousands) and the GINI index of income inequality (0= perfect equality and 100= perfect inequality). The GINI index was calculated by the compilation of income distribution data to extract a single number that represents the extent of income inequality within a country.

The numbers of species endangered like reptiles, mammals, fish, birds, trees and plants are used as dependent variables. These numbers of threatened species include full species that are critically endangered, endangered or vulnerable but exclude introduced species, species whose status is not sufficiently known (characterized by IUCN as "data deficient"), those known to be extinct and those whose status is not sufficiently known (characterized by IUCN as "not evaluated"). The source of the data is the World Resources Database and the data refer to the year 2004 for existing species and 2006 for endangered species[3]. Our sample consists of 71 countries[4].

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[2] It is worth mentioning that protected areas serve as a crucial function in protecting the earth's resources. However they have to cope with a number of challenges like external threats from climate change and pollution, irresponsible tourism, water resources extraction, increasing demand for land and infrastructure developments.

[3] World Resources Institute (2008). EarthTrends: The Environmental Information Portal Archived Data Tables (by Topic Area).

[4] The countries used are the one with full record (no missing values). Namely, Armenia, Azerbaijan, Bangladesh, Indonesia, Japan, Korea Rep, Kyrgyzstan, Malaysia, Nepal, Pakistan, Philippines, Tajikistan, Thailand, Uzbekistan, Vietnam, Bulgaria, Denmark, France, Germany, Greece, Ireland, Italy, Poland, Portugal, Romania, Russian Federation, Slovakia, Spain, Switzerland, Ukraine, United Kingdom, Algeria, Egypt, Israel, Jordan, Morocco, Tunisia, Turkey, Cameroon, Cote d'Ivoire, Ghana, Kenya, Mozambique, Nigeria, Senegal, South Africa, Tanzania, Zambia, Zimbabwe, Canada, United States, Costa Rica, Dominican Rep, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua,

Table 1 presents the descriptive statistics of the dependent variables into consideration. It can be seen that there are large differences between the mean and the median (first indication of asymmetry) and differences also in standard deviations, skewness and kurtosis. In all cases we have a positive value of skewness and the size of kurtosis is higher than 3, which implies huge mass at high levels and short tails at small amounts; this indicates highly asymmetric distributions. Thus the high mean values are due to a number of observations with high percentages of species in threat justifying the use of quantile regression. The kurtosis shows a leptokurtic type of distribution for the threatened species[5].

Table 1: Descriptive statistics of the species in threat

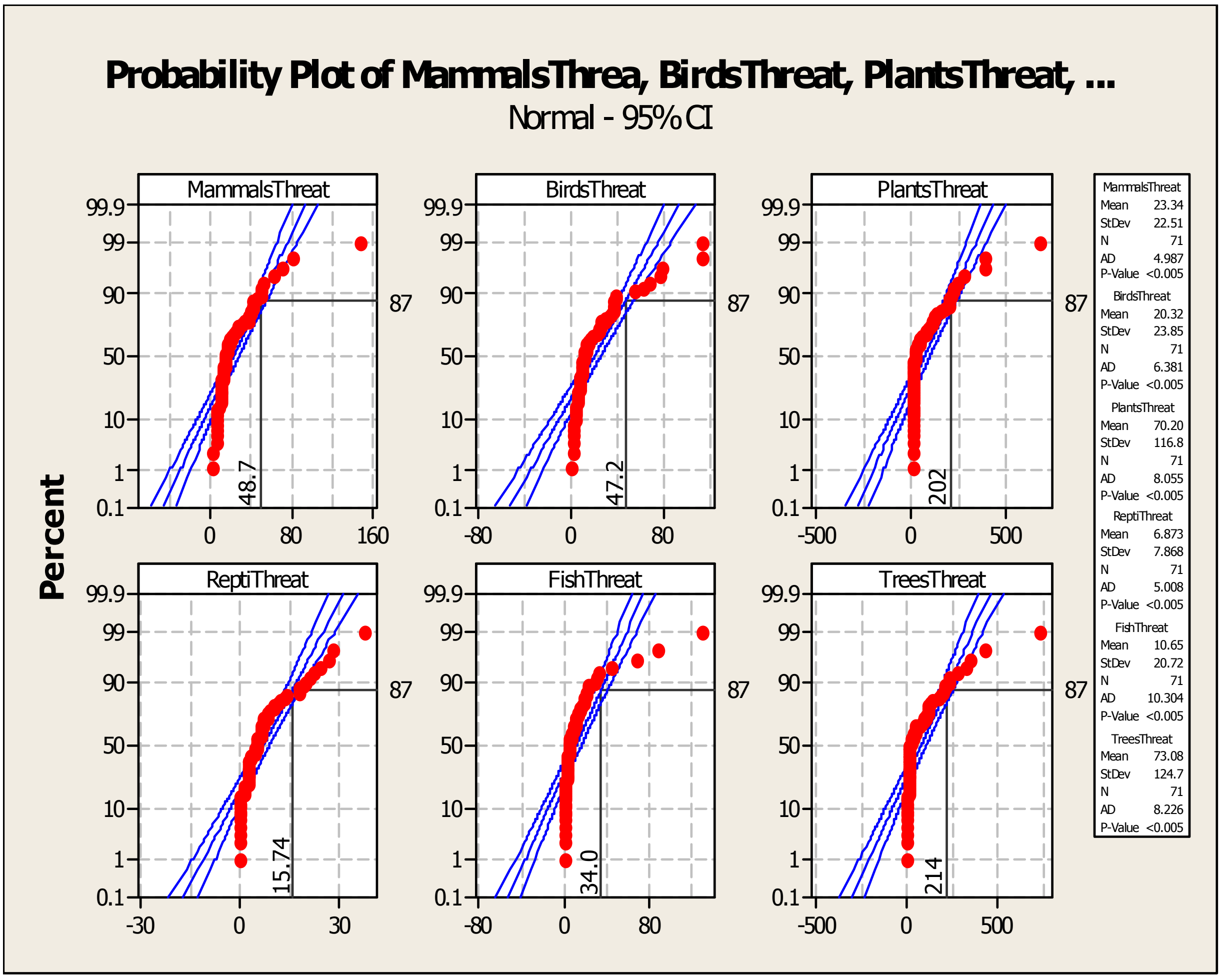
	BIRDS	FISH	MAMMAL	PLANTS	REPTI	TREES
Mean	20.32394	10.64789	23.33803	70.19718	6.873239	73.08451
Median	11.00000	3.000000	14.00000	12.00000	5.000000	11.00000
Maximum	114.0000	130.0000	147.0000	681.0000	38.00000	737.0000
Minimum	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000
Std. Dev.	23.85299	20.72066	22.51282	116.8225	7.868435	124.6703
Skewness	2.262963	3.843948	2.844754	2.759809	1.787826	2.859591
Kurtosis	8.347132	19.77271	14.48832	12.71648	6.067239	13.46692
JB Prob	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Figure 1 presents the probability plots of all the species in threat assuming normality. In all cases normality is rejected as the P-values of the Anderson-Darling test are less than the usual statistical levels leading to the rejection of the null hypothesis that the data follow the normal distribution.

Panama, Trinidad and Tobago, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela, Australia.

[5] According to the Box-Cox test the variables were used in levels (in most of the cases) and were not transformed in logs.

Figure 1: Probability graphical presentations of species in threat (assuming normality)



4. The proposed models

OLS estimates the effect of the explanatory variables on the mean of the conditional distribution of the dependent variable. This is obviously a strong simplification as regressors may not only determine the mean but may also influence other parameters of the conditional distribution of the dependent variable. Quantile regressions allow the examination of the entire conditional distribution of the dependent variable. At the same time it is less restrictive compared to the OLS (mean) regression as it allows the estimated parameters (slopes) to differ at different points of the conditional distribution of the dependent variable. As a nonparametric method, quantile regression imposes no functional form on the species endangered relationship and it is not sensitive to the presence of extreme values (outliers), a common problem when analysing data for developing countries. This may be justified as in quantile regressions we minimize the residuals and not their squares as in OLS.

Quantile regressions allow the estimation of various quantile functions of a conditional distribution where each quantile characterizes a particular (center or tail) point of the conditional distribution. Putting together a number of different quantile regressions gives us a more complete description of the underlying conditional distribution.

In simple words, in the OLS application the estimated parameters represent the change in the dependent variable caused from a unit change in the independents. The parameters of the quantile regression estimate the change in a specific quantile of the dependent variable due to a unitary change in the independent variable. This allows comparisons among the quantiles in terms of how much they are influenced from specific characteristics in relation to the other quantiles. This can be seen in the change in the magnitude of the coefficients. Quantile regressions are extremely useful when we face heteroskedasticity and/or no normality in the disturbance term (Buchinsky 1998).

Let us consider the quantile regression analytically. Assume a random variable Y with a probability distribution function given as

$$F(y) = \Pr(Y \leq y) \tag{1}$$

such as $0 < \lambda < 1$ when the i quantile can be defined as the lowest y that satisfies the condition $F(y) \geq \lambda$

$$Q(\lambda) = \inf\{y : F(y) \geq i\} \tag{2}$$

For a number of i observations for Y we have

$$F_i(y) = \sum_k l(Y_i \leq y) \tag{3}$$

Where l(z) takes the value 1 if Z true and 0 otherwise.

The corresponding empirical quantile is given as

$$Q_i(\lambda) = \inf\{y : Fn(y) \geq \lambda\} \tag{4}$$

The quantile regression extents the simple model including the explanatory variables X assuming linear specification for the conditional quantile of the independent variable Y given the values of the matrix P of the independent variables X. Specifically, ,

$$Q(\lambda \mid \mathrm{X}_i \beta(\lambda)) = \mathrm{X}'_j \beta(\lambda) \tag{5}$$

where
$$\beta(\lambda) = \arg mm_{\beta(\lambda)} \{\sum_j \rho_\lambda (\mathrm{Y}_j - \mathrm{X}'_j \beta(\lambda)) \tag{6}$$

The coefficients of the quantile regression are normally distributed for large samples (Koenker, 2005). Koenker and Bassett (1978) derive asymptotical results for normality for the quantile regression estimates in an independently and identically distributed (hereafter i.i.d.) formulation, showing that

$$\sqrt{i}(\hat{\beta}(\lambda)) - \beta(\lambda)) \sim \mathrm{N}(0, \lambda(1-\lambda) S(\lambda)^2 J^{-1}) \tag{7}$$

where
$$J = \lim_{i \to \infty} (\sum_j X_j X_j{}' / i) = \lim_{n \to \infty} (X'X / i) \tag{8}$$

$$S(\lambda) = F^{-1\prime}(\lambda) = \frac{1}{f(F^{-1}(\lambda))} \tag{9}$$

Where S(λ) is the quantile density function. We can calculate $S(\lambda)$ with the use of the Kernel density estimator (Powell 1986, Buchinsky 1995, Jones 1992). Specifically,

$$\hat{S}(\lambda) = \frac{1}{\left[(1/i) \sum_{j=1}^{i} c_i^{-1} L\left(\hat{\varepsilon}_j(\lambda) \big/ c_i \right)\right]} \tag{10}$$

where $\hat{\varepsilon}_j$ the residuals of the quantile regression.

The kernel estimation of the density function requires the specification of the bandwidth (C_i). If we define the coefficient vector of this procedure as

$$\beta = (\beta(\lambda_1)', \beta(\lambda_2)', \ldots, \beta(\lambda_\kappa)')' \tag{11}$$

then $$\sqrt{i}(\hat{\beta} - \beta) \sim \mathrm{N}(0, \Omega) \tag{12}$$

where $$\Omega_{ij} = \left[\min imum\left(\lambda_i, \lambda_j\right) - \lambda_i \lambda_j\right] H^{-1}(\lambda_i) J H^{-1}(\lambda_i) \tag{13}$$

In the case of i.i.d. Ω becomes $\Omega = \Omega_0 \otimes J$ where Ω_0 as representative element has

$$\omega_{ij} = \frac{\min(\lambda_i, \lambda_j) - \lambda_i \lambda_j}{f(F^{-1}(\lambda_i)) \cdot (f(F^{-1}(\lambda_j))} \tag{14}$$

Estimation of Ω may be done using the bootstrap method.

The test of slope equality was suggested by Koenker and Bassett (1982) and it is a robust heteroskedasticity test

$$H_o : \beta_1(\lambda_1) = \beta_2(\lambda_2) = \ldots = \beta_\kappa(\lambda_\kappa)$$

Where we have $(p-1)(k-1)$ restrictions in the coefficients. The corresponding Wald test is distributed as $\chi^2_{(p-1),(k-1)}$.

Similarly, the symmetry test was proposed by Newey and Powell (1987) and relies on the idea that if

$$\frac{\beta(\lambda) + \beta(1-\lambda)}{2} = \beta(1/2) \tag{15}$$ [6]

then we may estimate this restriction using the Wald test with H_0 having $p(k-1)/2$ restrictions and the Wald test is distributed as $\chi^2_{p(k-1)/2}$. This test compares the estimates of the first and third quantile with the median specification.

[6] As there is no clear positive relationship between the values of the quantiles and the estimated coefficients we may say that the conditional quantiles are i.i.d.

Another suggested method in cases of highly correlated independent variables or in the case of analysing fewer observations than variables or highly correlated dependent variables is the partial regression (PLS). This regression estimates models with more than one dependent variable in the same model formulation. This is achieved by reducing the number of explanatory variables and regressing the extracted components on the dependent variables and not on the original data. We include more that one dependent variable when the dependent variables are correlated between them.

5. Empirical results

Tables 2-4 present the OLS and the quantile regression estimates for the 10^{th}, 30^{th}, 50^{th}, 70^{th}, 90^{th} quantiles. The OLS (mean) regression estimates are presented for reasons of comparison with the quantile regression estimates. From Table 2 and comparing the quantile (median) with the OLS (mean) estimates there are significant differences in magnitudes. Specifically the number of endangered trees increase by (first quantiles and then OLS estimates in parentheses) 1.72 (2.02), 2.9 (3.88), 0.03 (0.019) and 0.09 (0.007) per unit increase in agricultural production, higher income inequality, higher level of CO_2 emissions and higher population respectively. Similarly and from table 3 it can be seen that the number of plants in threat increases by 1.653 (2.01), 2.52 (3.92), 0.022 (0.016) and 0.0065 (0.005) per unit increase in agricultural production, higher income inequality, higher level of CO_2 emissions and higher population.

Finally, from Table 4 we may see that the number of mammals in danger rises by 0.09 (0.23), 0.54 (0.46), 0.025 and 0.001 (0.0009) per unit increase in agricultural production, higher income inequality, higher level of CO_2 emissions and higher population. These comparison are more different is we compare the OLS (mean) with the other quantilies and especially the upper ant the lower ones asa shown in Figure 3. As a general comment we may say that the influence of the explanatory variables is higher in the case of plants and trees endangered followed by the mammals in threat. OLS overestimates the estimated parameters in the case of agricultural production and income inequality and underestimates in the case of population and CO_2 when we consider trees and plants threatened with a mixture with significant differences in magnitudes in the case of mammals endangered.

In Tables 2 and 3 the quantile regression shows that the influence of the agricultural production on the trees and plants in threat increases as we move from the 10^{th} to the 90^{th} quantile with exception in the case of the 70^{th} quantile. It is obvious that comparing the quantile estimates with those of OLS only the 90^{th} is comparable. Similar conclusions can be extracted for the other variables. For the GINI index we see an increase from the 10^{th} till the 90^{th} quantile. The OLS result is not comparable with those of the quantile regression with a similarity only in the 70^{th} quantile. In the same table there is a negligible change in the case of the other two variables (emissions and population) as we move across the quantiles.

In Table 4 and concerning the mammals in threat the picture is slightly different. Income inequality is the only variable increasing as we move from the 10^{th} to 90^{th} quantile. For the rest of the variables there is an unstable behaviour with increases and decreases in the quantiles as we move across them.

Table 2: Regression results with the trees endangered as dependent variable

Explanatory variables	OLS	Non-parametric quantile regression				
		10th quantile	30th quantile	50th quantile	70th quantile	90th quantile
Constant	-293.884 (-3.404) [0.0011]	-54.08 (-0.76) [0.4481]	-96.93 (-1.21) [0.2315]	-257.54 (-3.1) [0.0029]	-264.5 (-3.9) [0.0003]	-259.6 (-5.3) [0.0000]
Agricultural Production/c	2.016 (2.85) [0.0059]	0.254 (0.454) [0.6514]	0.467 (0.65) [0.5194]	1.72 (2.94) [0.0045]	1.61 (2.95) [0.0044]	2.145 (2.33) [0.0231]
GINI	3.878 (2.76) [0.0075]	0.766 (1.01) [0.3173]	1.41 (0.92) [0.1316]	2.9 (2.5) [0.0164]	3.98 (2.86) [0.0056]	5.02 (1.96) [0.0545]
CO_2	0.01923 (0.999) [0.3212]	0.0007 (0.012) [0.9904]	0.024 (1.57) [0.1216]	0.03 (3.46) [0.0010]	0.023 (3.5) [0.0008]	0.004 (0.61) [0.5431]
Population	0.00684 (2.339) [0.0224]	0.00013 (0.017) [0.9868]	0.003 (0.266) [0.7912]	0.009 (7.1) [0.0000]	0.0082 (8.2) [0.0000]	0.006 (7.3) [0.0000]
Quasi-LR statistic Wald slope equality test Wald symmetric test	27.21 [0.000] 58.94 [0.002] 16 d.f. 30.17 [0.067] 10 d.f.					

t-statistics in parentheses; P-values in [ ]

Table 3: Regression results with the plants endangered as dependent variable

Explanatory variables	OLS	Non-parametric quantile regression				
		10th quantile	30th quantile	50th quantile	70th quantile	90th Quantile
Constant	-294.94 (-3.67) [0.0005]	-32.96 (-0.46) [0.6453]	-101.28 (-1.374) [0.1742]	-234.1 (-3.009) [0.0037]	-246.56 (-4.011) [0.0002]	-260.78 (-4.74) [0.0000]
Agricultural Production/c	2.009 (3.044) [0.0033]	0.154 (0.274) [0.7849]	0.536 (0.804) [0.4243]	1.653 (3.04) [0.0034]	1.485 (3.008) [0.0037]	2.131 (2.51) [0.0145]
GINI	3.92 (2.99) [0.0039]	0.504 (0.65) [0.5195]	1.4 (1.64) [0.1052]	2.521 (2.32) [0.0234]	3.872 (2.6) [0.0117]	4.824 (2.025) [0.0470]
CO_2	0.016 (0.882) [0.3811]	0.0031 (0.0574) [0.9544]	0.026 (3.143) [0.0025]	0.022 (2.92) [0.0048]	0.018 (2.9) [0.0050]	0.0007 (0.11) [0.9148]
Population	0.0049 (1.81) [0.0761]	-0.00008 (-0.009) [0.9925]	0.003 (0.272) [0.7866]	0.0065 (5.5) [0.0000]	0.0058 (6.3) [0.0000]	0.004 (4.51) [0.0000]
Quasi-LR statistic Wald slope equality test Wald symmetric test	26.43 [0.000] 38.72 [0.001] 16 d.f. 19.88 [0.030] 10 d.f.					

t-statistics in parentheses; P-values in [ ]

Table 4: Regression results with the mammals endangered as dependent variable

Explanatory variables	OLS	Non-parametric quantile regression 10th quantile	30th quantile	50th quantile	70th quantile	90th quantile
Constant	-43.802 (-2.742) [0.0079]	-20.83 (-1.27) [0.2081]	-25.22 (-1.544) [0.1274]	-28.404 (-1.97) [0.0531]	-48.1715 (-2.8055) [[0.0066]	-45.703 (-4.391) [0.0000]
Agricultural Production/c	0.2255 (2.483) [0.0156]	0.1146 (1.8) [0.076]	0.08123 (1.073) [0.2872]	0.0896 (1.164) [0.2488]	0.2279 (2.532) [0.0137]	0.2903 (1.7077) [0.0924]
GINI	0.4619 (1.685) [0.097]	0.1156 (0.474) [0.6374]	0.3504 (1.212) [0.2297]	0.5433 (1.919) [0.0594]	0.7351 (2.073) [0.0421]	0.848 (1.514) [0.1347]
Log CO_2	5.6243 (4.0914) [0.0001]	2.6928 (1.77) [0.0821]	3.554 (2.34) [0.0224]	3.722 (2.99) [0.0040]	5.14 (2.9544) [0.0043]	5.0151 (2.894) [0.0051]
Population	0.000898 (1.6715) [0.0994]	0.00086 (2.53) [0.0139]	0.001135 (3.9953) [0.0002]	0.00099 (3.136) [0.0026]	0.000871 (2.765) [0.0074]	0.000496 (2.011) [0.0484]
Quasi-LR statistic		15.613 [0.0036]				
Wald slope equality test		30.153 [0.0170] 16 d.f.				
Wald symmetric test		16.138 [0.0950] 10 d.f.				

t-statistics in parentheses; P-values in [ ]

Standard errors of the quantile regressions are extracted by bootstrapping with 1000 replications. F values from Wald tests of equality of coefficients of specific independent variables across quantiles are also presented. These Wald tests of slope equality equal to 58.94, 38.72 and 30.153 for trees, plants and mammals in threat with P-values equal to 0.002, 0.001 and 0.017 respectively. We may conclude that the coefficients differ statistically across the values of the quantiles and the conditional quantiles are not similar. At the same time, the Wald test of quantile symmetry gives 30.167, 19.88 and 16.138 with P-values equal to 0.067, 0.03 and 0.8153 respectively. Closed related to the previous test we see that there is indication of deviation from symmetry. As already mentioned, these results may be justified as moving from the 10^{th} to the 90^{th} quantile, increasing influences can be observed for the agricultural production and income inequality in the case of trees and plants in threat but not for the pollution emissions and the population. The picture is different in the case of mammals in threat where except in the case of income inequality with an increasing behaviour the rest of the variables present a mixture of changes.

In Figure 2, the graphs of the quantile regression are done for the constant and the explanatory variables. The OLS estimate and its 95% confidence interval are plotted as horizontal lines. In each graph the regression coefficients show the influence of a unit change in the independent variable (holding constant the rest of the explanatory variables) on the specific levels of the quantiles of the dependent variable with a 95% probability level for the confidence intervals. The constant term can be interpreted as the estimated conditional quantile function of the endangered species with no influence of the explanatory variables. These graphs help us to see how changeable are those influences and show that a linear regression may be inadequate in terms of approaching these relationships. Thus using OLS provides less information compared to the use of quantile regressions.

Looking at figure 2 we can say that the variables agricultural production and income inequality (with the exception of the 90^{th} quantile) show an increasing influence as we move from the 10^{th} to the 90^{th} quantile. It is interesting to mention that in the cases of the GINI index OLS overestimates the estimated parameters till the 70^{th} quantile and then it underestimates the parameters. For the agricultural production underestimation takes place till the upper quantilies (80^{th}). In the case of population and CO_2 the picture is mixed. First OLS estimates underestimate (till the 35^{th}) then overestimate (till the 80^{th}) and then underestimate again. For the constant term there is a complete underestimation. A similar picture of behaviour is observed in the case of plants and mammals endangered[7]. The above imply that in this kind of environmental research we have to be careful because even if the average picture of behaviour seems reasonable the complete separation of countries (strata) may result to quite different results.

Figure 2: Graphical presentations of quantile process estimates for trees endangered (95% confidence interval)

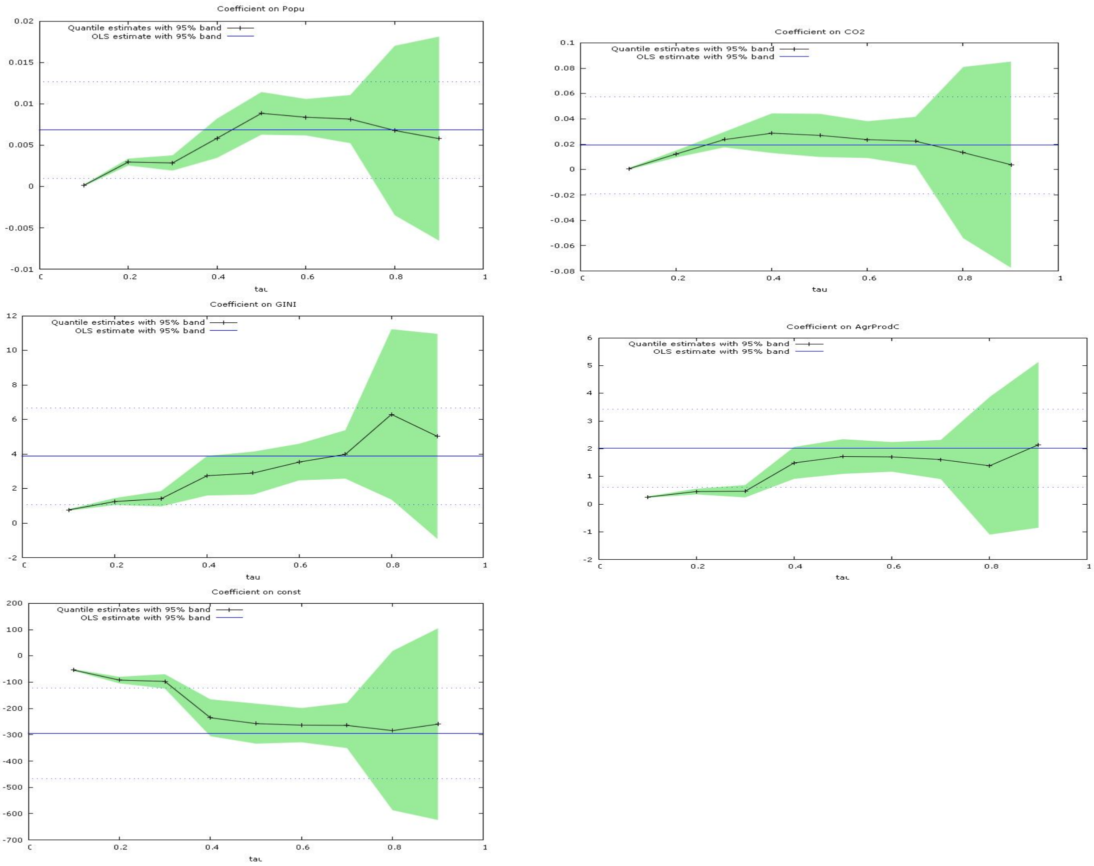


Table 5 presents the correlation coefficients among the dependent variables (birds, fish and reptiles in danger). All the coefficients are relatively high showing linearity among the variables. In Table 6 we may see the results of the partial

[7] Due to space limitations the graphs in the cases of plants and mammals in threat are not presented but they are available on request.

regression among the 3 dependent variables and the 6 independent (agricultural production, CO_2 emissions, income inequality, population, GDP/c, energy intensity)[8].

T**able 5:** Correlation coefficients of the dependent variables in the partial regression

Correlations: Birds in Threat, Reptiles in Threat, Fish in Threat

	Birds in Threat	Fish in Threat
Fish in Threat	0.670	
	0.000	
Reptiles in Threat	0.634	0.628
	0.000	0.000

Cell Contents: Pearson correlation
P-Value

First in the results of Table 6 it can be observed that the number of components of the optimal model (relying on the highest predicted R^2) equals to three. The table presents the analysis of variance per dependent variable and according to the optimal model. The P-values are zero and in every case less than the usual significance levels. In all cases there is sufficient evidence that the models are statistically significant. The coefficient of determination is low and equals to 0.261, 0.22 and 0.51 for the birds, reptiles and fish in danger respectively.

The column X-variance shows the percentage of variance of the independent variables which is explained by the model. In our case, the three components explain 68.11% of the variance of the independent variables.

Table 6: Partial regression results

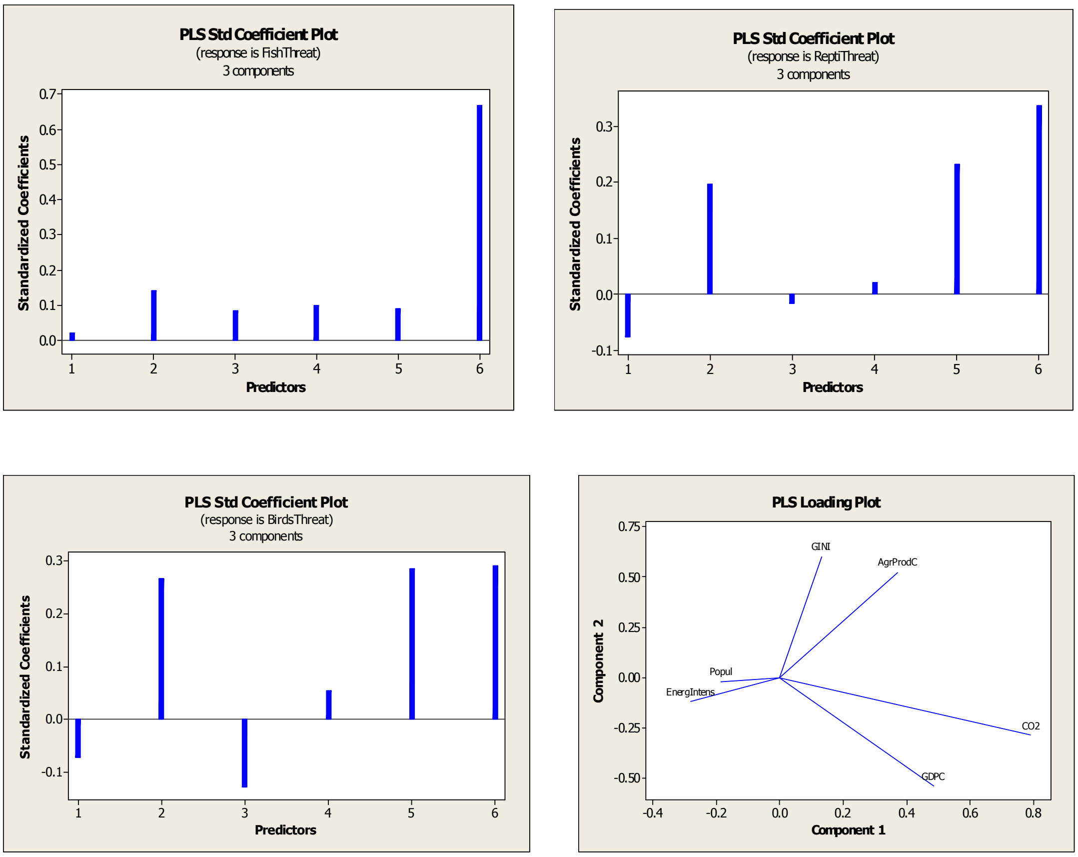
Number of components selected by cross-validation: 3
Number of components cross-validated: 6

	SSR	SSE	F	P	R-sq	X variance Explained
Birds in threat	10389.1	29438.5	7.88	0.000	0.27	0.6811
Reptiles in threat	944.04	3389.82	7.22	0.000	0.23	
Fish in threat	15340.6	14713.6	23.29	0.000	0.52	

[8] It is interesting that the addition of the variable protected areas reduces the percentage of the variance of the independent variables which is explained by the model from 68% to less than 40%.

The graphs in Figure 3 show the effect of each independent variable on the dependent variable. Specifically the graph on the top left corner shows that all the explanatory variables have a positive influence on the dependent variable fish in threat with the variable CO_2 emissions to have the most significant effect, with the variable income inequality to follow and the variable energy intensity to have the lowest effect.

Figure 3: Individual effects of independent variables on the dependent variable



Variable 1: Energy intensity
Variable 2: GINI index
Variable 3: GDP/c
Variable 4: Population
Variable 5: Agricultural production /c
Variable 6: CO_2 emissions

Similarly the graph on the top right corner and in the case of reptiles in threat the variables energy intensity and GDP/c have a very low negative influence. On the contrary the variables CO_2 emissions, agricultural production and income inequality as expressed by the GINI index have significant positive influence while population has a small positive effect.

The graph on the bottom left corner refers to the birds endangered and shows the same picture as in the case of birds but with higher negative effects for the variables energy intensity and GDP/c and almost equal positive influence for the variables income inequality, agricultural production and CO_2 emissions.

Finally in the graph on the bottom right corner we can see that the variables population and energy intensity have the smallest effect compared to the other variables.

6. Conclusions and policy implications

Relying on a sample of 71 countries and a number of economic and environmental variables we modelled and interpreted functionally the protection of various species in threat like reptiles, mammals, fish, birds, trees and plants. Due to the high asymmetric distribution of the dependent variables the mean regression cannot capture adequately the dimension of the species in threat. Comparing to the parametric estimates lead us to conclude that in such cases there exists a nonlinear relationship. The quantile regression is more preferable to the linear one as it enables us to look at the changes in the dependent variable in reaction to changes in the independent variables at different points of the distribution.

Specifically, as explained the quantile regression refers not to the mean influence of the independent variables on the mean value of the dependent variable but on a number of different quantiles. It also seems that explanatory variables have a substantial influence on species in threat either at the bottom or at the top of the distribution. In the case of trees and plants in threat the effect of the variables agricultural production (with an exception in the 70th quantile) and income inequality increases as we move from the 10th to the 90th quantile. On the contrary a stable influence can be observed for CO_2 emissions and population as we move along the quantiles. A mixture of changes is observed in the case of mammals in threat.

We have found that in the cases of the GINI index OLS overestimates the estimated parameters till the 70th quantile and then underestimates parameters while for the agricultural production underestimation takes place till the upper quantilies (80th). In the cases of population and CO_2 OLS first underestimates (till the 35th) then overestimates (till the 80th) and then it underestimates again the estimated coefficients. For the constant term there is a complete underestimation.

On the other hand, all the explanatory variables have a positive effect in the case of fish in threat with the variable emissions to have the most significant influence, the income inequality the second significant effect and the energy intensity the lowest power. In the case of reptiles endangered the variables energy intensity and GDP/c have a low negative effect. On the contrary, the variables emissions, income inequality and agricultural production have the most significant positive influence and the population to have a low positive effect. In terms of income inequality our results come in line and extend those of Mikkelson *et al.* (2007). Finally, the threatened birds show the same picture as the reptiles but with higher negative effects for the variables energy intensity and GDP/c and almost equal influence in the case of income inequality, agricultural production and emissions. It worth mentioning that population and energy intensity variables have the lowest effect compared to the others.

The policy implications are interesting. The vast population increase, urbanisation and extension of economic activities make the preservation of natural habitat and the solution of the problem really difficult in the near future. Given the limited capital for the environment and facing the great threat of extinction of some species, the decision makers have to put priorities making sure that the efforts of preserving biodiversity move to the right directions.

Quantile regression can be used effectively by ecologists. Due to complex interactions among organisms statistical distributions of ecological data have usually unequal variation. These interactions are not easily taken into consideration by statistical models. At the same time this unequal variation implies that there is not only a single rate of change (slope) that describes the relationship between a dependent and an explanatory variable measured on a subset of these factors. A solution to this limitation is the quantile regression, which estimates multiple slopes from the minimum to the maximum response and allows for a full picture of the relationships between response variable and regressors (Cade and Noon, 2003).

These slopes cannot be equal for all quantilies in cases where we have heterogeneous error distributions. This is the case in our analysis but it is expected to be the case in a range of ecological applications. Specifically complex forms of heterogeneous response distributions are expected in cases where important processes are not included in the model. In such cases we expect rates of changes of greater magnitude in the extreme quantiles (<30% or >70%) compared to the central estimates (50%). Using quantile regressions in models with unequal variances allow us to explore the associated effects with variables that may have been omitted as statistically insignificant on mean estimates. Our task is to tackle the large variation usually met in cases of detecting the relationship between ecological variables and the hypothesised casual factors not ascribed to random sampling variation.

The valuation of ecosystem services requires the integration of ecological knowledge with economics and the associated cooperation between ecologists and economists (Perrings and Walker, 1995). A number of actions with the formation of national policy for the preservation of every country's biodiversity, the establishment and operation of protected areas, the effective protection of species in threat, the conservation of genetic material of endemic plants and animals and the sensitiveness and the notification of the problem to all citizens and countries.

Biodiversity does not remain stable and for this reason a simple enumeration and recording is not sufficient. At the same time the scale of locality together with the global dimension of the problem make the formation of adequate policies difficult. This implies that the decision maker must take into consideration both the local and the national (global) scale and dimension of the problem in scheduling policies for the preservation of the environment.

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