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Analysis

Economic prosperity, biodiversity conservation, and the environmental Kuznets curve

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ABSTRACT

Many conservationists contend that economic growth and biodiversity conservation are incompatible goals. Some economists contest this viewpoint, arguing that wealthier countries have the luxury of investing more heavily in efforts to conserve biodiversity. Under this assumption, we expect a *U*-shaped relationship between per capita wealth and proportion of species conserved. We test this environmental Kuznets curve (EKC) using estimates of per capita income and deforestation rates (index of biodiversity threat) for 35 tropical countries. A prior analysis [Dietz, S., Adger, W.N., 2003. Economic growth, biodiversity loss and conservation effort. Journal of Environmental Management, 68:23–35] using conventional regression techniques failed to provide any support for the parabolic relationship predicted by the EKC hypothesis. Here, we introduce the use of quantile regression and spatial filtering to reanalyze this data, addressing issues of heteroskedasticity and spatial autocorrelation. We note that preliminary analysis using these methods provides some initial evidence for an EKC. However, a series of panel analyses with country-specific dummy variables eliminated or even reversed much of this support. A closer examination of conservation practices and environmental indicators within the countries, particularly those countries that drove our initial support, suggests that wealth is not a reliable indicator of improved conservation practice. Our findings indicate that an EKC for biodiversity is overly simplistic and further exploration is required to fully understand the mechanisms by which income affects biodiversity.

1. Introduction

The enormous scope of human activities (Vitousek et al., 1997; Pimm, 2001) poses a major threat to biodiversity. Globally, species are disappearing 1000s of times faster than they did historically (Pimm et al., 1995). Something on the order of 0.5% (Pimm et al., 1995) to 2% (Rosenweig, 2003) of all species are committed to extinction annually through tropical deforestation alone. Half of all species could be committed to extinction within the next few decades (Pimm and Raven, 2000; Myers and Knoll, 2001). Meanwhile, the human population continues to grow by ~2% annually (Cohen, 1995) and the global economy expands even faster (Raskin et al., 1998).

A number of scholars have argued that there is a conflict between economic growth and biodiversity conservation (Chambers et al., 2000, Czech, 2003; Trauger et al., 2003), suggesting that increased growth of the human economy implies increased overshoot of global biocapacity (Wackernagel et al., 2002). These conservationists contend that, while alleviating poverty in lesser-developed countries (Myers and Lanting, 1999; Adams et al., 2004), we must move toward a steady state economy (Czech, 2000; Myers, 2000) and thereby minimize the wholesale appropriation of natural ecosystems and loss of species (Chambers et al., 2000). Some economists take the opposing view that economic growth facilitates environmental protection (e.g., Grossman and Krueger, 1991, 1995; Beckerman, 1992; Hollander, 2003). More specifically, they argue that this is achieved when increases in *per capita* wealth free people to invest in environmental quality. They hypothesize an inverted *U*-shaped relationship between economic prosperity (per capita GDP) and environmental protection. (Here, however, we expect a *U*-shape, as positive environmental quality in our response variable is represented by higher values, as opposed to low values indicating high quality in several common applications of the EKC.) Testing this so-called environmental Kuznets curve (EKC) can help reconcile these conflicting views. (For a broad introduction to the EKC literature, see Ecological Economics' special issue 25(2) 1998, as well as the more recent literature reviews in Stern, 2004 and McPherson and Nieswiadomy, 2005).

In the context of biodiversity conservation, the EKC predicts that, given some original number of species, the proportion of those species conserved will be close to unity within countries at the low end of the prosperity continuum. As per capita GDP increases, species diversity will plummet. However, once a certain economic level is attained, countries are presumably wealthy enough to invest in conservation practices and this should cause the proportion of species conserved to rise again (Fig. 1). Evidence for this parabolic EKC would suggest that continued increases in prosperity could help solve rather than exacerbate the biodiversity crisis. However, whether an EKC for biodiversity exists remains open to question. The EKC, derived from a landmark paper on income inequality (Kuznets, 1955) and adapted to

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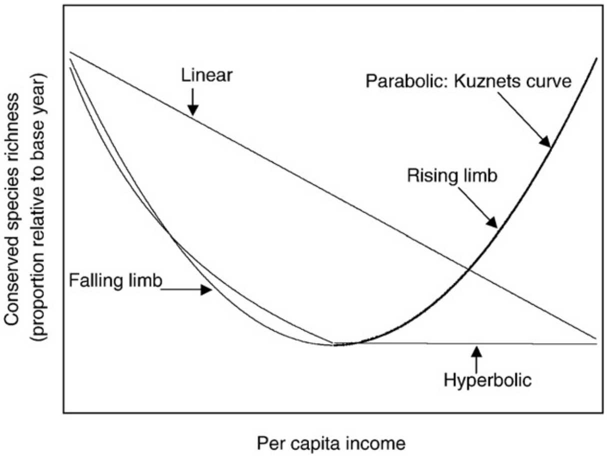

Fig. 1. Three hypothetical forms of the relationship between per capita income and proportion of species conserved within a given country (after Fig. 1 in Dietz and Adger, 2003). Falling and rising limb portions of the parabolic environmental Kuznets curve (EKC) are indicated.

the question of environmental degradation by Grossman and Krueger (1991), has been applied to a variety of environmental indicators. However, it has generally been judged to be valid only in cases where environmental damage is reversible (reviewed by Dietz and Adger, 2003). For this reason, Dietz and Adger argued that an EKC for biodiversity was a theoretical impossibility. They argued that anthropogenically driven extinctions vastly outpace speciation events, rendering biodiversity losses irreversible. Czech (2008) elaborates this criticism, further adding that restoration of habitats, which might lead to species recovery, is exceptionally difficult, a fact which we do not dispute.) Dietz and Adger thus chose not to test for a parabolic relationship between wealth and biodiversity. Czech (2008) offers further critique of the conceptual weaknesses of an EKC for biodiversity, most notably in outlining the competitive exclusion problem imposed by the laws of physics and ecology which places undeniable limits on growth. In the case of biodiversity, this problem is exacerbated as economic growth tends to lead directly to competitive exclusion of nonhuman animals and plants, but the accompanying environmental problems also cause indirect biodiversity declines (Czech, 2008).

Nonetheless, while many conservationists argue that the EKC has essentially been dismissed from academic circles (Stern, 2004; Czech, 2008), those same scientists acknowledge that policy makers (and many economists) have not yet reached the same conclusion. We agree with Czech's argument: that the necessary policies to preserve biodiversity will never be achieved unless the policy community first recognizes the fundamental conflict between economic growth and biodiversity (2008). For these reasons, and because we argue that an EKC for biodiversity is theoretically possible (albeit perhaps very difficult to achieve), we reconsider here the evidence for an EKC for biodiversity. We begin by noting that Dietz and Adger (2003) inadvertently obscured a parabolic relationship by the way they graphed their data (Fig. 2a). A strongly parabolic pattern becomes evident when the *y*-axis is rescaled (Fig. 2b). Next, we extend the analysis of their dataset using an alternative to standard regression, specifically quantile regression (Koenker, 2005). We challenge the theoretical objection of Dietz and Adger (2003) to the possibility of an EKC and we test specifically for a parabolic relationship. An initial analysis provides support for such a relationship. However, we question whether this support is just an artifact of ecologically unsustainable economies among the richest countries. To explore this possibility, we perform a series of panel analyses including country-specific dummy variables. These analyses eliminate or even reverse most of the initial evidence for a *U*-shaped curve.

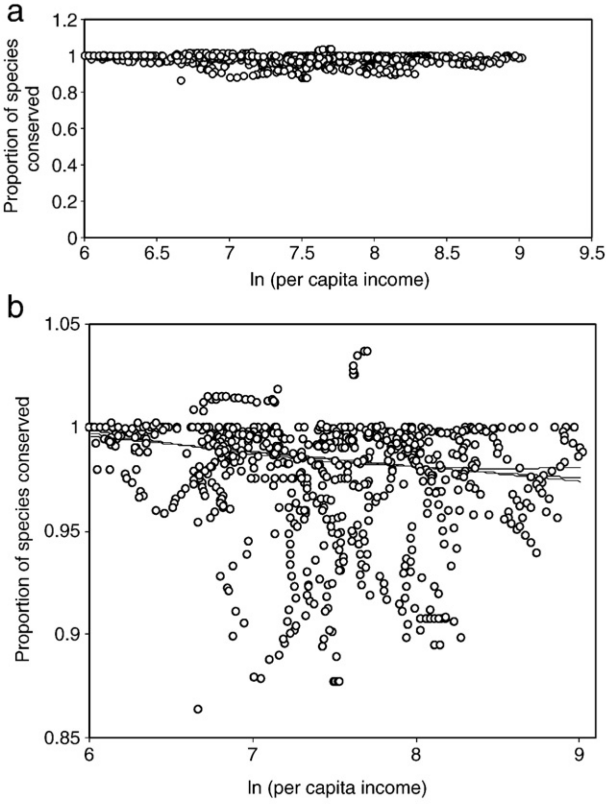

Fig. 2. Panel (a): reconstruction of the graph of Dietz and Adger (2003) using the same data and scaling as presented in their paper. The predicted proportion of species conserved (Eq. (2)) as a function of per capita GDP for 35 tropical forest countries, 1972–1992. Panel (b): rescaling the same data emphasizes parabolic pattern. The least-absolute-deviation regression curve, corresponding to the 50th quantile, is shown for each simple model (parabolic (Eq. (3)), hyperbolic (Eq. (4)), and linear (Eq. (5))).

Table 1
Comparison of data and methodology between Dietz and Adger (2003), on which this study was based, and the current study, Mills and Waite (2009).

	Dietz and Adger, 2003	Mills and Waite, 2009
Data		
Countries	35 tropical countries from Central America, South America, Africa, and Asia	35 tropical countries from Central America, South America, Africa, and Asia
Range	1972–1992	1972–1992
Dependent variable	Proportion of species conserved	Proportion of species conserved
Economic variables	GDP per capita	GDP per capita, (GDP per capita)^2
Other variables	Population change, population density, linear time trend (year), forest area, democracy index	Population change, population density, linear time trend (year), forest area, democracy index, spatial covariates
Methodology		
Models	Linear, hyperbolic[a]	Linear, hyperbolic, parabolic
Spatial autocorrelation correction	None	Borcard–Legendre PCNM spatial filtering
Regression	OLS (conventional regression)	Least-absolute-deviation quantile regression
Panel analyses	Random and fixed effects (country-specific)	Fixed effects (both country-specific and region-specific analyses)

[a] Dietz and Adger (2003) do not test the parabolic (EKC) model because they argue that an EKC for biodiversity is a theoretical impossibility.

2. Methods

Readers should note that, for consistency in our reanalysis, we have tried to mimic the general methodology of Dietz and Adger (2003) as closely as possible. We do so despite the fact that we are not in total agreement with their methods. In particular, the choice and number of countries examined, the choice of additional variables included, the use of 1972 as the base year for time series, and the use of 0.25 as the z-value for species–area calculations give rise to a variety of concerns. We address some of these issues in subsequent sections and propose to consider others in future work. (For a quick comparison of data and methods between this paper and Dietz and Adger, see Table 1. For more information on the specifics of data collection and compilation, please see Dietz and Adger, 2003).

2.1. Tropical deforestation and biodiversity losses

We use the species–area relationship (SPAR), $S=cA^z$, from island biogeography theory (MacArthur and Wilson, 1967) to predict the proportion of species persisting following deforestation. In this classic equation, S is the number of species persisting at equilibrium (i.e., when the opposing forces of extinction and colonization reach the balance point), A is area of habitat, and c and z are constants. Log-transformed, this relationship is a linear equation, $\log(S)=\log(c)+z\log(A)$, where log (c) is the y-intercept and z is the slope. Parameter z thus describes how species richness changes with loss (or gain) in the amount of habitat available. A larger z-value translates into a larger number of predicted extinctions for a given area loss. Many empirical studies of the SPAR in an island archipelagic context have yielded z-values clustering around 0.25 (Rosenzweig, 1995; Pimm and Raven, 2000). Following Dietz and Adger (2003), we assume $z=0.25$ and use estimates of annual deforestation to predict the proportion of species remaining as a function of the proportion of land area remaining.

The proportion of species conserved following habitat loss can be predicted by dividing the expression for the equilibrium species richness based on the amount of habitat remaining at time t,

$$S_t = cA_t^z$$

by the expression for the original species richness,

$$S_0 = cA_0^z,$$

which yields:

$$\frac{S_t}{S_0} = \left(\frac{A_t}{A_0}\right)^z. \tag{1}$$

We let $\varphi(i,\ t)$ represent the predicted proportion of species conserved in country i as a function of the amount of tropical forest remaining in year t in relation to the amount in the base year, 1972. Substituting into Eq. (1), the ratio of the predicted number of species conserved in country i in relation to the species richness in the base year is:

$$\varphi(i,t) = \frac{S_t(i)}{S_{1972}(i)} = \left(\frac{F_t(i)}{F_{1972}(i)}\right)^{0.25}, \tag{2}$$

where F is the amount of tropical forest cover in country i in a given year. The left hand side of this expression is the dependent (response) variable for all analyses.

2.2. Quantile regression

Conventional regression methods, as used by Dietz and Adger (2003), estimate rate of change in the *mean* of the distribution of the response variable, as a function of one or more predictor variables. Fitted curves may be linear, hyperbolic, parabolic, and so on. Regardless of which functional form is used, the function is fitted only to the mean of the distribution. This conventional approach may be inadequate because it ignores all other regions of the distribution. This approach may be especially inadequate in cases where variance in the response variable is heterogeneous. Such is the case in our dataset. A quick visual assay of the data is enough to demonstrate this fact and suggest the need for a more thorough analysis (Fig. 2b). Fortunately, an alternative method, called quantile regression, can be used to estimate the relationship between one or more predictor variables and the response variable for all parts of the distribution (for an excellent primer see Cade and Noon, 2003). Here, we use quantile regression to explore how the predicted proportion of species conserved varies as a function of per capita wealth and other predictor variables.

We begin by considering simple models where per capita income G (data from Penn World Table, Heston et al., 2002) is the only predictor variable. We model the predicted species richness conserved (relative to the base year), as expected under the EKC hypothesis, as a parabolic function of G:

$$\varphi(i,t) = \alpha + \beta_1 \ln G(i,t) + \beta_2[\ln G(i,t)]^2 + \varepsilon(i,t). \tag{3}$$

We also model the proportion of species conserved using a hyperbolic function,

$$\varphi(i,t) = \alpha + \beta_1[1/\ln G(i,t)] + \varepsilon(i,t), \tag{4}$$

and a linear function,

$$\varphi(i,t) = \alpha + \beta_1 \ln G(i,t) + \varepsilon(i,t). \tag{5}$$

Next, we consider three full models, incorporating several additional predictor variables used by Dietz and Adger (2003) (though other potentially important explanatory variables should be considered in future work (see, for example, Brown and Pearce, 1994 for detailed exploration of various factors influencing deforestation)). We model the proportion of species conserved, as expected under the EKC hypothesis, as a parabolic function,

$$\begin{aligned}\varphi(i,t) = \alpha &+ \beta_1 \ln G(i,t) + \beta_2[\ln G(i,t)]^2 + \beta_3 C(i,t) \\ &+ \beta_4 P(i,t) + \beta_5 T(i,t) + \beta_6 F(i,t) + \beta_7 D(i,t) + \varepsilon(i,t)\end{aligned} \tag{6}$$

where C is change in human population as a percentage of the previous year's population (Penn World Table); P is population density in people per hectare (Penn World Table); T represents the year; F is forest area in hectares (data from FAO Production Yearbook); and D represents the scaled democracy value assigned to each country based on political rights and civil liberties (indices taken from Freedom House annual comparative survey tables available at http://www.freedomhouse.org to create a scale from 2 to 14, with 14 being most democratic).

We also model the proportion of species conserved using a hyperbolic,

$$\begin{aligned}\varphi(i,t) = \alpha &+ \beta_1[1/\ln G(i,t)] + \beta_2 C(i,t) \\ &+ \beta_3 P(i,t) + \beta_4 T(i,t) + \beta_5 F(i,t) + \beta_6 D(i,t) + \varepsilon(i,t)\end{aligned} \tag{7}$$

and a linear function,

$$\begin{aligned}\varphi(i,t) = \alpha &+ \beta_1 \ln G(i,t) + \beta_2 C(i,t) + \beta_3 P(i,t) \\ &+ \beta_4 T(i,t) + \beta_5 F(i,t) + \beta_6 D(i,t) + \varepsilon(i,t)\end{aligned} \tag{8}$$

By including Eqs. (3) and (6), we test for a parabolic relationship between per capita income and predicted proportion of species conserved, as predicted by the EKC hypothesis. By contrast, Dietz and Adger considered only the hyperbolic (Eq. (7)) and linear functions (Eq. (8)). They chose not to include the parabolic model (Eq. (6)), arguing that the rising limb (Fig. 1) of the EKC was a theoretical impossibility. They thus chose not to perform a direct test of the EKC. They implied that the rising limb could occur only if the rate of speciation were to exceed the rate of extinction due to deforestation. We dispute this reasoning.

To see why the rising limb is possible after all, consider the definition of $\varphi(i, t)$. This dependent variable is *not* the predicted number of species remaining at time t relative to those extant in the base year. Instead, it is the predicted number of species persisting *ultimately* (i.e., once equilibrium is reached) relative to those extant in the base year. The key is the lag between deforestation and extinction. The relaxation to an equilibrium number of species in a remnant forest fragment can be modeled as an exponential decay ($=\exp[-kt]$), where the annual proportionality constant, k, may take a value on the order of 0.025 (Brooks et al., 1999). At this rate, it would take over 25 years to realize half of the predicted extinctions due to the deforestation during any given year. It would take nearly a century (~92 years) to realize 90% of the predicted extinctions. For larger areas of remnant forest, the rate of extinction is reduced and so it may take more than a century to realize half of the predicted extinctions (Ferraz et al., 2003). This gradual decay suggests that the rising limb is possible. If a country were to get rich quickly and begin a reforestation program, many species committed to extinction by past deforestation could conceivably be spared. (Even natural forest recovery can allow for recolonization, although it may take decades for secondary forest to become suitable habitat for forest-obligate species (Ferraz et al., 2003; but see Harris and Pimm, 2004). There is also considerable literature describing how non-forest habitats may support forest species (see, for example, Daily et al., 2001). This would provide yet another avenue for recovery of species committed to extinction.) That is, *commitment to* extinction is partially reversible and the rising limb could result. We thus include the parabolic functions (Eqs. (3) and (6)) in our analysis.

Throughout all analyses, we use least-absolute-deviation quantile regression to quantify the parabolic, hyperbolic, and linear relationships, usually for all quantiles, 1st, 2nd, …, 99th. We evaluate whether the predicted proportion of species conserved is a demonstrably parabolic function of per capita wealth, as predicted by the EKC hypothesis, for any portion of the distribution. We use Blossom Statistical Software (2003.02) to perform the analyses. We use the regression quantile rank-score test (Koenker and Machado, 1999) to compare pairs of full vs. restricted models and report p-values (two-tailed) based on 10,000 iterations of this goodness-of-fit test.

2.3. Panel analysis

The dataset includes a time series for each country, with series comprising similar numbers of years. To analyze this unbalanced panel, we perform a series of formal panel analyses, using fixed effects models. In doing so, we examine whether differences among countries (and regions) were the driving factor behind our initial evidence for an EKC.

We assume, initially, that each country could have its own separate influence and we thus include a dummy variable N_i specific to each time series:

$$\begin{aligned}\varphi(i,t) = {} & \alpha + \beta_1 \ln G(i,t) + \beta_2 C(i,t) + \beta_3 P(i,t) \\ & + \beta_4 T(i,t) + \beta_5 F(i,t) + \beta_6 D(i,t) + N_2 + N_3 + \ldots + N_{35} + \varepsilon(i,t).\end{aligned} \tag{9}$$

Note that one country's time series is arbitrarily left out of the equation to serve as a reference group. We conduct the panel analysis for all quantiles, 1st through 99th.

We then perform a regional panel analysis, assigning dummies to regions, rather than countries:

$$\begin{aligned}\varphi(i,t) = {} & \alpha + \beta_1 \ln G(i,t) + \beta_2 C(i,t) + \beta_3 P(i,t) \\ & + \beta_4 T(i,t) + \beta_5 F(i,t) + \beta_6 D(i,t) + R_2 + R_3 + R_4 + \varepsilon(i,t).\end{aligned} \tag{10}$$

Here, R_2 refers to Central America, R_3 to South America, and R_4 to Asia. (Africa serves as the reference group.) These regions are assigned based on the groupings provided in Dietz and Adger (2003). Ideally, these regions should serve to form groups of countries ecologically similar enough to share a single fixed error effect. By assigning region-specific dummies, we evaluate whether differences among regions can produce potentially misleading support for the EKC.

Next, to make inferences about each region, we perform a separate analysis for each of the four regions. We do so for all quantiles both with and without country-specific dummy variables. This analysis evaluates whether differences among countries within a region can produce potentially misleading support for the EKC.

2.4. Spatial autocorrelation

Finally, we use spatial filtering techniques to evaluate whether the above analyses were confounded by spatial autocorrelation (for a unique example of how to account for autocorrelation in EKC analyses see McPherson and Nieswiadomy, 2005). This is necessary due to the fact that many of the countries in our dataset are distinguishable from one another only by geopolitical borders. In many cases, neighboring countries are very similar in terms of their ecosystems and species and may therefore be more closely related to each other than to the rest of the dataset.

Failure to correct for these spatial relationships can inflate Type 1 errors, causing us to detect a significant relationship where in fact there is none. (Diniz-Filho et al., 2003 provide an excellent introduction to the theoretical background and ecological implications of spatial autocorrelation; see also Dale and Fortin, 2002.) Some ecologists have even gone so far as to suggest that the spatial structure inherent in ecological data creates 'red herrings' and results in systematic bias in our interpretation and understanding of ecological processes (Lennon, 2000). While not all ecologists share this extreme view, there is growing acceptance of the notion that ecological analyses should be corrected for spatial autocorrelation.

Here we use a particular method of spatial correction known as spatial filtering. This method is particularly useful as it analyzes spatial structure and produces a series of covariates which account for this structure and can then be easily incorporated into any statistical model (see Griffith and Peres-Neto, 2006 for an introduction to the use of spatial filters in ecology). This allows spatial filtering to be flexibly applied with a wide range of analyses. Here, for instance, spatial filtering allows us to address spatial structure in tandem with quantile regression.

We use an equidistance cylindrical projection map in ArcGIS (version 9.2) to establish a center point for each country in the dataset. We then input the latitude and longitude data for these centroids into SAM (Rangel et al., 2006) and create a matrix of pairwise distances for all countries. To ensure that we use the shortest distance between each pair of countries, we create two matrices: the first uses the standard map centered at 0° longitude; the second uses a map re-centered at 180° longitude (effectively allowing us to calculate distances around the back of the globe). For each distance pair, we select the shorter of these two distances to create our final matrix.

We then use R (R Development Core Team, 2008) to apply the Borcard–Legendre principal coordinates of neighbor matrices (PCNM) spatial filtering technique (Borcard and Legendre, 2002). The resulting spatial covariates S_1 and S_2 are added to the model as additional variables, such that Eq. (3), for example, becomes:

$$\varphi(i,t) = \alpha + \beta_1 \ln G(i,t) + \beta_2 [\ln G(i,t)]^2 + \beta_3 S_1 + \beta_4 S_2 + \varepsilon(i,t) \tag{11}$$

We then perform all analyses a second time with the spatial covariates included.

3. Results

3.1. Non-panel analysis

Fig. 2b shows the fitted curves, at the 50th quantile, for all three simple models, parabolic, hyperbolic, and linear (Eqs. (3)–(5)). The three regression curves are virtually indistinguishable. This graph highlights the limitation of using the conventional approach of fitting a functional form to the mean of the distribution, where variance in the response variable is heterogeneous.

Fig. 3 shows the fitted curves for the 5th, 10th, 50th, 90th, and 95th quantiles. All three models yield similar results for the upper quantiles. At lower quantiles, however, the parabolic model clearly provides the best description of the distribution of the response variable. This is what we might expect under the EKC hypothesis. Extreme data in the lowest quantiles could be expected to map nicely onto a parabola; however, we have no a priori reason to expect all of the data to cluster around a single parabola. Rather we might expect variation in countries' experiences and growth trajectories to create a distribution of data extending throughout the space between the line $y = 1$ and parabolas fitted to lower quantiles.

In this exploratory (non-panel) analysis, the simple parabolic model (Eq. (3)) was significant ($p < .05$) for all quantiles, 2–97, and was significantly better ($p < .05$) than the linear model (Eq. (5)) for all lower quantiles, 1–50, and for 71–73. This model outperformed the linear and hyperbolic (Eq. (4)) models for the lowest quantiles. Similar patterns were found for the full models (Eqs. (6)–(8)): the parabolic model was significant for every quantile and significantly better than the linear model for quantiles 2–66 and 71.

3.2. Panel analysis

Results are reported for the dataset excluding India, Sri Lanka, and an extraneous Bangladesh point. We excluded these countries' time series because they contained outliers that appear to be anomalous byproducts of political events (e.g. border conflicts, newly independent countries) or reporting errors. In most cases, analyses were also performed with these countries' time series included. However, because the results were qualitatively similar, we describe just one set of findings.

When country-specific dummy variables were included, the parabolic model was significant ($p < .05$) for all quantiles and significantly better ($p < .05$) than the linear model for many quantiles (3, 5–7, 18–86). However, the sign of the coefficient for G^2 was negative for all quantiles in both tests, indicating an inversion of parabolic shape, from *U*-shaped to hump-shaped. This analysis, therefore, provides no support for the EKC.

When region-specific dummy variables were included, the parabolic model was significant for many quantiles (2–77, 94–96) and significantly better than the linear model for quantiles 1–78. Additionally, the parabola exhibits the proper EKC curvature (i.e., coefficient of $G^2 > 0$) for many quantiles (1–84, 89–93, 98). Thus, we found strong support for the EKC when region, rather than country-specific, dummies were included. This support held even when we removed from the analysis South America, the region with the largest dummy variable coefficient (coefficient of $G^2 > 0$ for all quantiles; parabolic model significant: 3–99; significantly better than linear: 2–69, 75).

Fig. 4 describes patterns of curvature (*U*- versus hump-shaped) and significance (parabolic versus linear model) for all quantiles. Results are shown for eight analyses, one with and one without country dummies for each of the four regions. Shading indicates a *U*-shaped, EKC-like curve (i.e., coefficient of $G^2 > 0$). All regions except South America exhibit some range in which the model without dummy variables is both significant and curved in the EKC direction. However, with country-specific dummies included, only Africa exhibits this kind of support for the EKC and not for any of the lower quantiles. The other three regions provide an abundance of evidence for curvature in the opposite direction from that predicted by the EKC hypothesis.

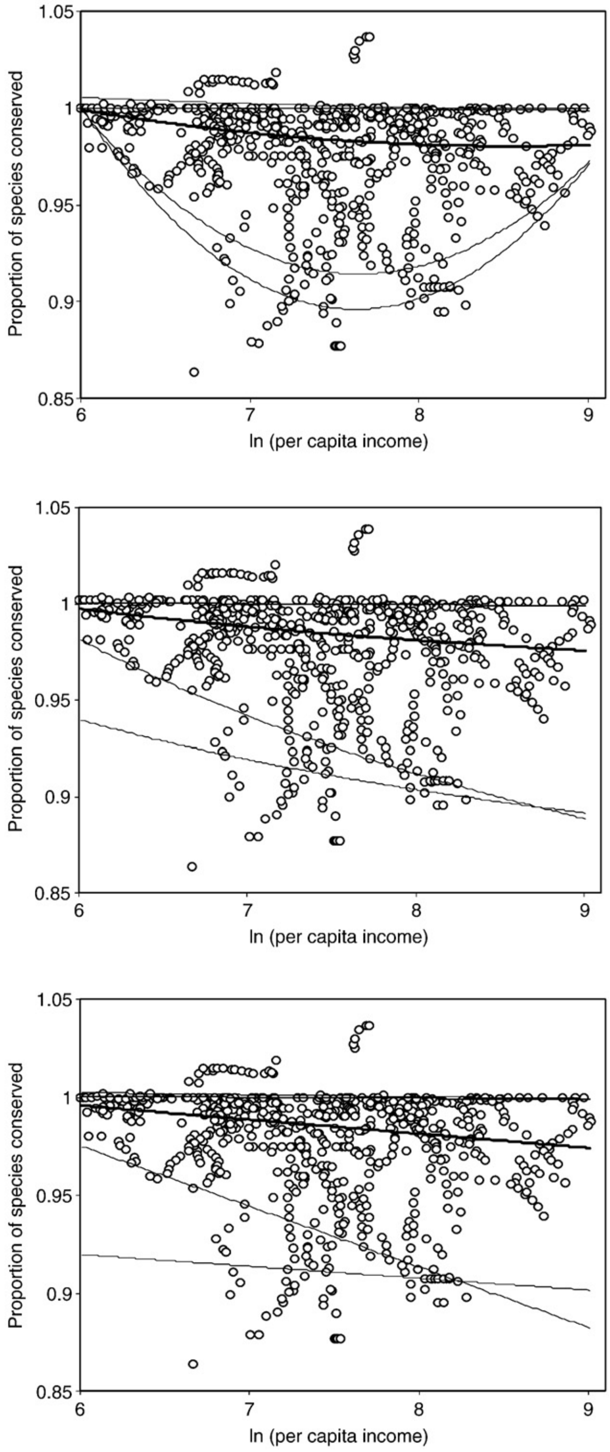

Fig. 3. Quantile regression curves for each of the three simple models (Eqs. (3)–(5)): parabolic (top), hyperbolic (middle), and linear (bottom). Starting from bottom of each graph, curves represent the 5th, 10th, 50th, 90th, and 95th quantiles. Data points predicted by Eq. (2).

3.3. Spatial autocorrelation

Finally, the inclusion of the spatial covariates in our models reveals that there are indeed spatial relationships among neighboring

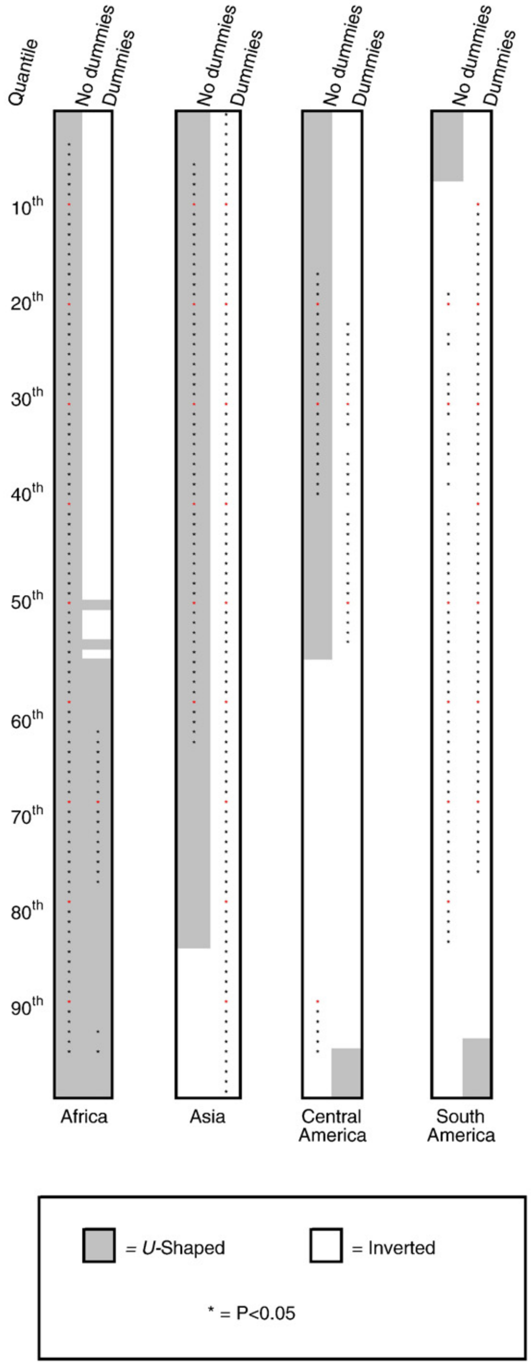

Fig. 4. Summary of results of quantile regression with and without country-specific dummy variables for each of the four regions. Gray shading indicates a *U*-shaped parabola, consistent with the EKC; absence of shading indicates a hump-shaped parabola, in conflict with the EKC. Asterisks indicate that parabolic model was significantly better than linear model ($p<0.05$). Red asterisks appear at multiples of 10 to aid visual inspection.

countries that are not accounted for in any of our previous models. Our results show that the addition of the spatial filter yields models that are significantly better ($p<.05$) than the original models. When spatial covariates are added to the country-specific dummy analysis, the parabolic model was significant for quantiles 1–94 and significantly better than the original (no spatial filter) country-specific model for quantiles 4–9, 11–76, and 78–79. For the region-specific dummy model, the addition of spatial covariates produced a model that was significant for quantiles 2–64 and 79–98 and significantly better than the original region-specific model for quantiles 15–97. However, the inclusion of the spatial covariates does not qualitatively change the results or direction of curvature of any of the previous models.

4. Discussion

We began with the non-panel approach to simplify our initial explorations into quantile regression, but the decision to include it here rests on the importance of the theoretical questions it raises. In particular, if use of country-dummies reveals that differences between countries drive the support for the EKC (i.e. inclusion of country-dummies eliminates support for the EKC by accounting for differences between countries), which countries are most influential, and what differences are driving the relationship? Though this is perhaps unconventional, we feel that it is appropriate. A thorough exploration of the intricacies of the EKC relationship is absolutely necessary, particularly as the EKC is implemented in policy decisions that affect biodiversity conservation as well as human interests.

Our initial analysis seemed to provide support for an environmental Kuznets curve (EKC) for biodiversity (Fig. 3). This support is consistent with the possibility that increased per capita GDP leads to a higher proportion of species conserved via corresponding reduction in deforestation rate. A few of the richest countries exhibit relatively slow deforestation over a two-decade period. Superficially, this suggests that biodiversity conservation could be improved through economic growth.

However, when we performed panel analysis with country-specific dummy variables included, this support was eliminated or even reversed, as has been found in other studies (Moran, 2005). The reversal of evidence was especially dramatic for Asia. Significance was obtained for every quantile when dummy variables were included, but every quantile exhibited an inverted, hump-shaped curve (Fig. 4), the opposite of what we expect from the EKC hypothesis. Central and South America too provided evidence against the EKC when country-specific dummies were included. Even the strong support for the EKC in Africa was lost for all of the lower quantiles when country dummies were included. Because including country-specific dummy variables routinely eliminated support for the EKC, it appears that differences among countries really were the driving force behind our initial support (Fig. 2) as well as that provided by the analysis including region-specific dummies. Thus, we have no reason to believe our initial support for the EKC reflects robust improvement in forest conservation with increasing per capita wealth *within* countries.

The question remains, though, why we found any support for the EKC, even in our initial analysis. If adding dummy variables reveals that support for the EKC was driven by differences between countries, which countries created this support? To address this question, we focus on the five richest countries, those presumably most responsible for the rising limb (Fig. 5). We argue that these countries have not moved toward genuinely better conservation practices. First, despite their relative prosperity, these countries have continued to practice deforestation. Between 1990 and 2000, Mexico and Malaysia lost more of their forest than did over half of the 35 countries, Venezuela lost 4.2% of its remaining forest, Brazil lost 4.1%, and even Gabon experienced a net loss of 0.5% (FAO, 2001). Second, none of the countries driving the rising limb (Fig. 5) experienced a rebound in forest cover between 1972 and 1992. Third, two of these countries have oil-based economies. In 2002, 69% of Gabon's and 73% of Venezuela's export economy was based on oil (World Bank, 2004). Hypothetically, these countries could resort to forest clearance when their oil revenues dwindle. Finally, four of the five richest countries have the largest ecological footprints among the 35 countries (Loh and Wackernagel, 2004). The amount of ecologically productive land and water used in these countries exceeds the "fair Earthshare" (1.8 ha/person). Only Gabon's footprint (8th largest) falls below this threshold of sustainability, reflecting Gabon's low human density. Thus, our initial support for the EKC reflects reduced but ongoing deforestation

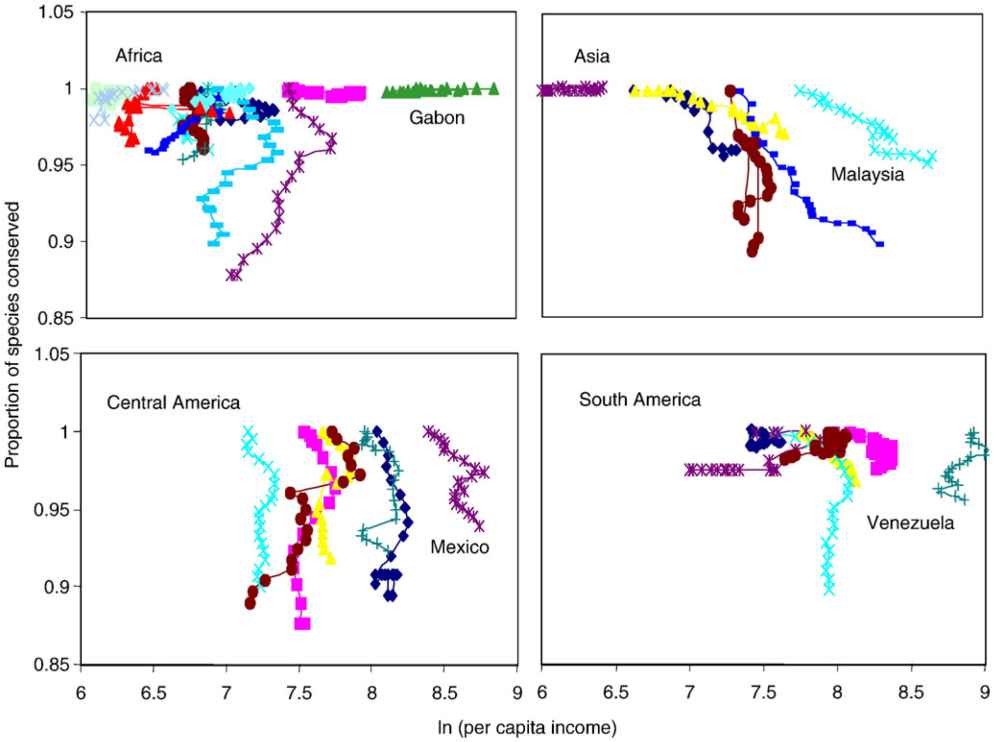

Fig. 5. Relationship between per capita income and predicted proportion of species conserved for each country within each of the four regions. Each country's time series is depicted by a different symbol and represents the interval 1972–1992. The richest country within each region is labeled (India, Sri Lanka, and one anomalous point for Bangladesh have been removed from the upper right panel, Asia).

in the most prosperous countries, whose footprints exceed the global biocapacity. This initial support appears to be doubly deceptive. It does not seem to reflect legitimate gains in conservation either within or beyond the richest countries' borders.

Had our initial support for the EKC been upheld by the panel analyses, we would still have called for a cautious interpretation. Even positive results should not be too hastily considered evidence that increasing wealth is good for biodiversity conservation. The mere presence of support for or against the EKC tells us nothing about the causal relationship between per capita GDP and species conservation (and even less about the connection between economic growth in the aggregate (GDP) and biodiversity). As we point out, evidence does not suggest that countries with high per capita income are actually exhibiting improved conservation practices. Because these countries are continuing to deforest their lands, we can easily surmise that income from timber production, etc. may be a large factor contributing to their increased wealth.

After all, to the extent that increasing wealth comes about through liquidation of natural capital (i.e., clearance of forest) (Naidoo, 2004), evidence for the rising limb would not imply genuinely improved conservation. To see why increasing wealth is achieved through liquidation of natural capital, consider the connection between natural trophic structure and the human economy as laid out by Czech (2000, 2008). Much as higher consumers in the natural world are dependent upon the primary consumers and producers below them, light manufacturing depends upon heavy industry which in turn depends upon agricultural production and resource extraction. Similarly, there is an associated *amount* of lower level production required to sustain the upper levels, thus growth at the top of the chain implies either growth at the bottom (i.e. deforestation) or increased efficiency in the modes of production (Czech, 2000). Unfortunately, the laws of physics preclude us from ever attaining perfect efficiency, so growing economies will necessarily entail increases in resource consumption. (Even so-called information economies fall prey to this dilemma, as information is only valuable as it applies to the market, and thereby, to other sources of production (Czech, 2008)). Thus, if wealth (either in the aggregate or per capita) is gained via deforestation, it is hard to argue that getting richer leads to improved forest conservation.

4.1. Future directions

Future work should explore more fully the nature and implications of the relationship between economic growth (as indicated by increasing GDP) and biodiversity conservation, as well as the relationship between prosperity (as indicated by increasing per capita GDP) and conservation. Only two prior studies have provided any support for an EKC for biodiversity, and that support was limited to birds (Naidoo and Adamowicz, 2001; McPherson and Nieswiadomy, 2005) and mammals (McPherson and Nieswiadomy, 2005). Data availability prevented McPherson and Nieswiadomy from examining other taxa, but Naidoo and Adamowicz (2001) were able to consider four additional groups (plants, amphibians, reptiles, and invertebrates). For each of these, Naidoo and Adamowicz found the opposite of what we expect from the EKC: the predicted number of threatened species *increased* with increasing prosperity (Clausen and York (2008) find the same result for freshwater and marine fish species). Even the optimistic forecast for birds and mammals seems dubious. McPherson and Nieswiadomy (2005) are careful to point out that their results indicate only the *possibility* that an EKC may exist for these taxa. Moreover, while richer countries appear to be doing a better job of protecting birds and mammals, the richest countries' economies place them well above the global sustainability level (Loh and Wackernagel, 2004). We speculate that these countries do a good job of protecting birds and mammals *within* their national boundaries (Czech et al. (1998) demonstrate that these two taxa in particular are advantaged in terms of both their social construction and the amount of political power endowed to them by various conservation groups), but high levels of consumption in developed nations suggest that internal protection may come at the expense of expropriating resources from, and thereby jeopardizing, natural ecosystems and species beyond their borders.

This hypothesis highlights a potential weakness in focusing on nation-states as a unit of analysis (Clausen and York, 2008; though Rudel and Roper (1997) argue that the imprecision inherent in the use of the nation-state is offset by the value obtained by considering the influence of country-wide socioeconomic conditions on deforestation). Moreover, the idea that richer countries create an illusory appearance of improved conservation through exploitation of poorer ones is consistent with world systems theory and international political economic theory, both of which assert that global structure promotes the redistribution of resources from producers in the global periphery (less developed countries) to consumers in the core (developed countries) (Hoffman, 2004; Ehrhardt-Martinez et al., 2002). Ehrhardt-Martinez et al. (2002) find no connection between world systems theory and deforestation in their analysis (they attribute their evidence of a deforestation EKC to urbanization, democracy, and growth of the service sector); however, this result may be skewed by the fact that their dataset contains no developed countries (and therefore no "core" nations).

We propose that a full account of each country's consumption (for example, accounting for a nation's total forest product consumption rather than just in-country deforestation) may eliminate the existing evidence for the rising limb (see Rothman, 1998 for an analysis of the role of consumption in EKCs). Future work could use import/export data to evaluate whether local gains in forest conservation are offset by global losses.

We believe the discussion herein is widely applicable to the question of economic growth and biodiversity in general (i.e. we would hypothesize that consumption is a key factor regardless of which aspect of biodiversity you investigate). However, we have truly examined only deforestation and therefore the forest (and specifically tropical moist forest) species associated therewith. We would venture to assert that this subset of species represents a disproportionately important component of all species (after all, Wilson (1988) estimates that at least half of the world's species are likely contained within moist tropical forests). Nonetheless, readers should keep in mind that deforestation is only one aspect of the environmental degradation that accompanies growing economies, and that this variable inherently excludes a wide range of species and ecosystem types, each of which have unique properties and contribute to the functioning of the global system as a whole. Work that explores other ecosystems and drivers of biodiversity decline would undoubtedly further our understanding of the relationship between economic growth and biodiversity.

We also promote work on the following topics. First, hypothetical reforestation scenarios could be used to evaluate the potential for sparing species already committed to extinction. Second, our analysis assumed that the natural world of the future would comprise many island-like habitats. We thus assumed that the future species–area relationship (SPAR) could be predicted using a z-value (0.25) for the island-archipelagic scale, but Rosenzweig (2003) recently argued that the natural world of the future would comprise a collection of biogeographically representative reserves. Accordingly, the biogeographic region would be the appropriate scale and the SPAR should be predicted using a higher z-value (~0.9–1.0). Thus, the predicted number of species committed to extinction via deforestation will be nearly proportional to the amount of habitat lost. This would make it harder to justify economic growth via deforestation. Finally, we have implicitly assumed that the habitat lost through deforestation is of representative quality. However, conservation efforts are underway to set aside biodiversity hotspots (Myers et al., 2000; Myers, 2003; Mittermeier et al., 2005), areas with high species richness and irreplaceable ecosystems. Taking these complexities into account will help refine our understanding of the relationship between economic prosperity and biodiversity conservation at multiple scales.

5. Conclusion

We promote the use of quantile regression in EKC analyses. Though we cannot account for all of the factors contributing to the complex relationship between per capita income and biodiversity, quantile regression provides a more complete picture of the relationship than does conventional regression. We think the use of quantile regression (this study) and autoregressive techniques (this study and McPherson and Nieswiadomy, 2005) represent vast improvements in EKC analysis, and we encourage future workers to combine these tools.

We argue that the presence or absence of evidence for an EKC is insufficient information on which to draw conclusions regarding the relationship between income and biodiversity. In particular, we suggest that rich countries are likely fueling their own consumption by expropriating resources from poorer nations. This claim requires further investigation. Current data are sufficient, however, to confirm that the rich countries in our dataset were not characterized by improved conservation. In light of this fact, this study strengthens the arguments being made by Stern (2004), Rothman (1998) and Czech (2008), that the EKC is not a robust representation of the relationship between economic growth and environmental quality. We encourage further exploration into the mechanisms by which differences between countries may drive apparent support for a biodiversity EKC, but strongly discourage any use of a biodiversity EKC *per se* in policy applications.

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