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A Cross-Countries Analysis of Biodiversity Loss and Tourism Demand: Evidence From Count Models

Abstract

The purpose of this study is to examine the relationship between tourism arrivals and the global incidence of biodiversity loss, measured by the probability of the extinction of species of plants, mammals, birds, and fish while controlling for other relevant covariates: protected areas, agrarian production's share in GDP, crop production, energy intensity, and population levels. This study is designed around cross-sectional data from 2018 in 178 countries across the world. The biodiversity loss–tourism arrivals nexus is assessed in this study by the count model estimation. We adopted negative binomial and hurdle negative binomial regressions. The findings showed the existence of a positive relationship between tourism arrivals and some species extinction variables. Tourism demand is responsible for an excessive degree of biodiversity loss in the case of mammals and birds. The findings of this study suggest that an overdispersion test due to count data constraints should be taken into account when examining the link between biodiversity loss and tourism in a cross-sectional analysis.

Keywords: biodiversity loss, tourism arrivals, count models, cross-sectional data, world countries

1. Introduction

Over recent decades, international tourism has experienced continuous expansion, becoming one of the largest and fastest-growing service industries in the world. Despite the uncertain global economic outlook: the risks of terrorism, and the recent disruption due to the COVID-19 super-shock, the number of international tourists is still steadily growing. From only 25 million arrivals worldwide in 1950, the number exploded to 1.5 billion by 2019 (World Tourism Organization [UNWTO], 2017, 2020). In other words, in 68 years, global tourism has multiplied 56-fold; and there is no doubt that contemporary traveling mankind puts enormous pressure on biodiversity.

Human land use is the main driver of terrestrial biodiversity loss (Sun et al., 2022). Some biological species, subject to exhaustion by exploitation due to anthropogenic factors, can, in a general sense, regenerate to some degree, such as some fishes, birds, mammals, and plants. To date, the natural growth rate of the population of major species was tasked with sustaining the lives of the majority of species. However, as we discuss in this paper, the state of species that are in peril of extinction depends on the eliminating forces due to the demands of international tourism. By that, we confirm that the ability of species to reproduce and possibly be augmented is a dynamic process and full of complexity; which will be abstracted, and we will not be addressing it in this paper as it is hard to foresee in the conditions of the global interconnections of multiple dependable habitats of various species (predator-prey games in multiple millions of biospheres where those species live and so on) what is waiting for us in the future. Therefore, at the forefront of our research, we will set up one sole topic, and that is: how tourism arrivals across the world impact biodiversity loss.

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A sense of loss is experienced if the biodiversity of the planet is reduced (Sinclair & Stabler, 1997); we argue in this paper that future generations will, inevitably, pay the environmental toll due to dogma centered upon perpetual economic growth; the over-tourism that has flourished in the last decades impacted, and indeed may wound biodiversity. Hypertrophied tourism puts a lot of strain on environmental sustainability and will inevitably lessen the quality of life of humankind, although, in the short term, it appears to be beneficial. Both sides are at a profit from a myopic standpoint to utilize imminent benefits: demand and the supply agent(s). In other words, mass intercontinental travel by jet and resort owners increases instant utility by generating demand that meets supply in the neo-classical sense of the economic jargon. Hence, Hall (2010a) stresses the importance of research on tourism's role in extinction and habitat loss, biological invasion, climate change, and biodiversity.

In this paper, we further assume that the state of each species can be indefinitely maintained if, and only if, the extinction of its genome due to the presence of tourism would be less or equal to its ability to regenerate in the future. The main policy implication here draws on Habibullah et al. (2016), which is entwined with regenerating potential, and it is upon that thesis the tourism industry depends on the very existence of biodiversity. Hence, the same author holds that conservation should, accordingly, become the essential factor for business sustainability.

After searching for more recent similar literature relevant to this topic, which has proliferated in recent years, we found subsequent papers based on the idea of a linkage between tourism demand and biodiversity loss. One of the studies examined the causal relationships between international tourism, biodiversity loss, environmental sustainability, and specific growth factors under the premise of sustainable tourism in Austria by using long-run time series data from 1975 to 2015 (Malik, Shah & Zaman, 2016). In their paper, the authors argued that intervention in the relationship between biodiversity and tourism cannot and should not only be based on considerations of measurable impacts of tourism on biodiversity alone because legitimacy, feasibility, and effectiveness should be taken into account in actions (Van der Duim & Caalders, 2002). Other authors find the impact of tourism among the major causes for biodiversity loss in the Socotra Archipelago (Yemen) which is globally recognized for its outstanding biodiversity and endemism, designated on this basis a UNESCO World Heritage Site in 2008, along with the degradation, pollution and invasive species impact (Damme & Banfield, 2011). Hall (2010b) outlines the ambiguous role of tourism, which has long been cited as a justification for conserving biodiversity via the establishment of national parks and reserves, although it also contributes to biodiversity loss as a result of direct habitat change and human activity, as well as more indirectly via the introduction of exotic species and environmental change. Sustainable tourism, which one author equates with ecotourism, has been identified as one of the measures required to achieve biodiversity conservation both in situ, e.g., by establishing protected areas, and ex-situ, e.g., by improving zoos' conditions (Catibog-Sinha, 2010). In the view of Brandt and Buckley (2018), ecotourism is growing rapidly in biodiversity hotspots because of its promise to achieve both economic growth and environmental conservation; the same authors reviewed the literature for empirical evidence that ecotourism protects forests and found counterintuitive results that indicate ecotourism leads to deforestation. Nyaupane and Poudel (2011) explored the relationships between biodiversity conservation, livelihood improvements, and tourism development using the appreciative inquiry approach as a research tool around the Chitwan National Park, Nepal, and came to conclude that tourism helps change local people's attitudes toward the conservation of biodiversity and reduce people's dependence on natural resources. According to Hall (2010c), steady-state tourism is a system that encourages qualitative development but does not aggregate quantitative growth to the detriment of the natural capital, of which biodiversity is an inherent part. In the case of tourism's long-run development path, more does not mean better, and growth does not mean bliss forever. Gössling (1999), in his attempt to reveal how ecotourism can contribute to safeguarding biodiversity, used a cost-benefit analysis of the ecosystems richest in species diversity, i.e., tropical rainforests, which led to the conclusion that non-use values often outweigh the values of conventional uses (clear-cutting, pasture, etc.), but are hardly considered in development decisions. The study, which tries to identify threats against biodiversity and conservation across protected areas in Kenya, found that tourism is not a major primary threat at all; paradoxically, this paper suggests that the other threats identified may represent a threat to Kenya's tourism industry (Okello & Kiringe, 2004). Other authors examined the relationship between international tourism, air pollutants, and ecological biodiversity underlying the premises of the environmental Kuznets curve in the panel of 35 tourists-attracting countries from 1995 to 2016, using the panel fixed effect and panel two-stage least square regression technique for robust inferences (Qureshi et al., 2019). Fletcher (2019) examines several ways in which the prospect of the loss of "natural" resources is promoted as the basis of the tourism experience: disaster tourism; extinction tourism; voluntourism; development tourism; and, self-consciously, Anthropocene tourism. Tovar-Sánchez, Sánchez-Quiles, and Rodríguez-Romero (2019) highlighted that the environmental risk of chemical damage in the Mediterranean Sea is likely to be exacerbated due to the massive influx of tourists and its densely populated coasts, as well as the basin's limited exchanges with the ocean, the high residence time of surface waters, and its oligotrophic waters. The result obtained by Yassin, Aralas, and Basa (2020) implied that an increase in the tourism density index impacts the environmental performance index in 10 ASEAN countries. Hoppstadius and Sandell (2018) notice that studying concrete examples of situated cases of sustainable development efforts in terms of biosphere reserves can contribute greatly to the ongoing discussion about which development approaches in tourism are seen as sustainable. Hoogendoorn (2021) explore current and future destinations across South Africa where cultural groups are threatened, fauna and flora are on the brink of extinction, and landscapes are devaluing. Some travelers, Wolf-Watz (2014) remarked, reject traveling by air on environmental grounds in a desire to distance themselves from contemporary urban society. The drivers of biodiversity loss — including land-use change, intensive agriculture, and ecosystem degradation or unsustained tourism — are a murky prediction that may increase the risk to humans from emerging infectious diseases (Dinneen, 2020). Newsome and Hughes (2018) argue that visitors place a complex array of demands on conservation reserves, implicating by it biodiversity losses. Tickner et al. (2020) in their paper propose an Emergency Recovery Plan to bend the curve of freshwater biodiversity loss. Mazor et al. (2018) talk in their work about various drivers of biodiversity loss that need urgent realignment to match predicted severity and inform policy goals. Other authors (Horváth et al., 2019) deliver hard evidence by carrying out a longitudinal study that habitat loss always translates into species loss. Focusing on protecting both food security and biodiversity loss, Scherer et al. (2020) emphasize the need for a strategic approach directed at minimizing harm and avoiding reaching catastrophic tipping points for humanity. Facemire and Bradshaw (2020) utilized the emergent theory of mismatched property rights to address the problem of biodiversity loss. Bhuiyan et al. (2018) examined the impact of greenhouse gas (GHG) emissions on ecological footprint, habitat area, food supply, and biodiversity in a panel of thirty-four developed and developing countries over the period of 1995–2014 and found that GHG emissions had affected the biodiversity indicators.

The following research question is asked in this paper: what forces determine the probability of a biodiversity loss, along with the impact that comes from tourism arrivals in a representative set of countries allocated across the world? The paper is organized as follows. The next section begins by mapping out the research strategy, including the conceptual framework and short critiques of previous research on the same topic, statistical modeling, dataset, and variables. The following section presents and discusses the data analysis/empirical results, and the final section concludes by suggesting implications for economic policy and further research.

2. Methodology

Few analysts have already taken into consideration linear regression models when working with non-categorical data on biodiversity loss impacted by tourism demand around the world (Habibullah et al., 2016). Linear regression, particularly Ordinary Least Squares (OLS) regression, leans on specific assumptions which are often not satisfied in biodiversity data loss. Ordinary Least Squares assume that the dependent variable has a continuous value, is normally distributed (e.g., not skewed), and is linearly related to the independent variables (McClendon, 1994). However, biodiversity (data) loss as a negative externality in a macro setting does not adhere to these assumptions inherent in the OLS. These events with the loss of some of the species are rare and eventually occur within each of the four subsets with which we are dealing, yet that incidental extinction is counted in the various regions around the globe and registered in world statistics every year. Thus, species termination episodes are mostly distributed as a unit with non-negative values. Furthermore, lower values are more prevalent across countries on the world map territory; no biodiversity loss evidenced by zero occurrences is less common, but it occurred here and there across some countries. That quanta of observations features in measurement to give formal meaning to our criticism—implied in it is the specific kind of distribution, which violates the aforementioned assumptions of OLS regression that had been applied by Habibullah et al. (2016). Consequently, if we embrace OLS modeling, redo the work with the same method and update the data testing, we are risking that the estimate of the impact of exogenous factors and its statistical significance may well be either an over- or underestimate. Neither is acceptable to us for a plain reason—the OLS model, in such a case, will deliver spurious results.

Poisson, negative binomial, and hurdle regression models, all of which come under the umbrella of more general count models, are calibrated approximately to be superior models. In our opinion, they are optimal, and we intend to analyze count data of diversity loss with it. The "rare events" that nature encounters in species extinction will be controlled for in the formulas of Poisson, negative binomial, or hurdle regression. In any case, these models vary in respect of their presumptions of the conditional mean and variance of the dependent variable. Poisson models assume that the conditional mean and variance of the distribution are equal, but the last assumption may not be fitting for our diversity loss data. If that fact is true, we will likely adopt a negative binomial regression (or possibly its hurdle variety model) that does not assume an equal mean and variance. That model, particularly, is correct as well for overdispersion in the data, which is when the variance is greater than the conditional mean (Osgood, 2000; Paternoster & Brame, 1997).

2.1. Poisson model

The most common technique employed to model count data is the Poisson regression. It encompasses a usual feature of equality of mean and variance. Its probability mass function is given as:

$$\Pr\,(Y = (y_i|\mu) = \frac{e^{-\mu}\mu^{y_i}}{y_i};\, y_i = 0{,}1{,}2, \dots.$$

where yi signifies the irregular variable of the count response, that is, the number of threatened species (Cameron & Trivedi, 1999); subscript *i* denotes particular species of plant or mammal/bird/fish extinction.

The Poisson regression model is regularly alluded to as a benchmark to demonstrate modeling count data. For non-negative count outcomes, a model with Poisson distribution is much more suitable than an OLS linear model (Cameron & Trivedi, 1998). The self-evident skewness is the visual yield of such recurrence conveyance, known as Poisson distribution.

2.2. Negative binomial model

The negative binomial (NB) distribution is a two-parameter distribution combining the Poisson distribution and the Gamma distribution features (Gamma–Poisson mixture). It relaxes the assumption of the equality of mean and variance, thus evidencing unobserved heterogeneity in the count data (Cameron & Trivedi, 1999; Baum, 2010; Yesilova et al., 2010; Reese, 2016). Its probability mass function is given as:

$$\Pr\,(Y = (y_i|\mu, \alpha) = \frac{\Gamma(\alpha^{-1}+y_i)}{\Gamma(\alpha^{-1})\Gamma(y_i+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\mu+\alpha^{-1}}\right)^{y_i}$$

The mean and variance of the negative binomial distribution are E $[y|\mu, \alpha] = \mu$ and V $[y|\mu, \alpha] = \mu(1 + \alpha\mu)$, where α is the dispersion parameter (if $\alpha > 0$ and $\mu > 0$). Extraordinary cases of the negative binomial include the Poisson ($\alpha = 0$) and the geometric ($\alpha = 1$) (Cameron & Trivedi, 1999).

In the ***hurdle Poisson*** *(HP) model*, the primary portion is the hurdle at zero, which addresses the "few" or "more" zero results better than the distributional presumption of the Poisson model, and the second part governs the truncation part or positive outcomes (Winkelmann & Zimmermann, 1995; Cameron & Trivedi, 1999; Lam et al., 2006). Given a variable yi the HP probability distribution is given as:

$$\Pr(y_i = 0) = 1 - p, \qquad 0 \leq p \leq 1$$

$$\Pr(Y = y_i) = p\,\frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!}, \mu > 0;\ \mu_i = 1,2,\ldots$$

where μ is the mean of the Poisson model, when $(1–p) > \exp(–\mu)$, the information contains more zeros relative to the Poisson model.

The ***hurdle negative binomial*** *(HNB)* is adopted when the hurdle model is suitable, and the data show overdispersion (Cameron & Trivedi, 1999; Chipeta et al., 2014). The HNB model is given as:

$$\Pr(y_i = 0) = 1 - p, \qquad 0 \leq p \leq 1$$

$$Pr(Y = y) = \frac{p}{1 - \left(\frac{\Gamma}{\mu + \Gamma}\right)^{\Gamma}} \frac{\Gamma(y + \Gamma)}{\Gamma(r)y!} \left[\frac{\mu}{\mu + \Gamma}\right]^{y} \left[\frac{\Gamma}{\mu + \Gamma}\right]^{\Gamma}$$

$$\Gamma, \mu > 0; \quad y = 1,2 \ldots$$

The mean and variance of the HNB distribution are given as μ and $\mu(1 + \mu/\Gamma)$, respectively, and the quantity $\mu(1 + \mu/\Gamma)$ is a measure of dispersion (Yesilova et al., 2010.)

Different diagnostical tests were applied to assess overdispersion and compare model fit. Thus, we will test for overdispersion. Overdispersion in the Poisson regression was assayed by the Lagrange multiplier statistic (Silva & Covac, 2000). The model selection criterion was based on the maximum likelihood estimates of the model parameter, using the log-likelihood and the Information Criterion (IC)—Akaike (AIC) and Bayesian (BIC). A lower IC esteem suggests that the model is of superior fit (Pan, 2001; Vrieze, 2005). In addition to using IC values to evaluate the models, Vuong's tests were also used for model comparisons.

The Vuong (1989) non-nested test is based on a comparison of the predicted probabilities of two count models that do not nest. Examples include comparisons of NB versus ordinary Poisson, HP versus ordinary NB, or HP versus HNB. A large, positive test statistic provides evidence of the superiority of model 1 over model 2, while a large, negative test statistic is evidence of the superiority of model 2 over model 1. To control for the Type I error rate for the several model comparisons that were made, $p < 0.01$ was used as a criterion for indicating a statistically significant result.

3. Data analysis

Poisson, NB, HP, and HNB models were each fitted into the data with count regression modeling, which contains a sample of cross-sectional countries. The essential purpose was to treat the world as an all-encompassing set of nations.

First, this study is based on a cross-sectional design where data from 2018 were sourced and collected from World Bank development indicators across various countries (World Bank, n.d.). However, because of lost information (missing data here and there), we sifted the primary ambition to test the set of 216 nations. Thus, second, after filtering the primary sample, the diminished sample contained 176 nations or observations substantially robust enough for assessment.

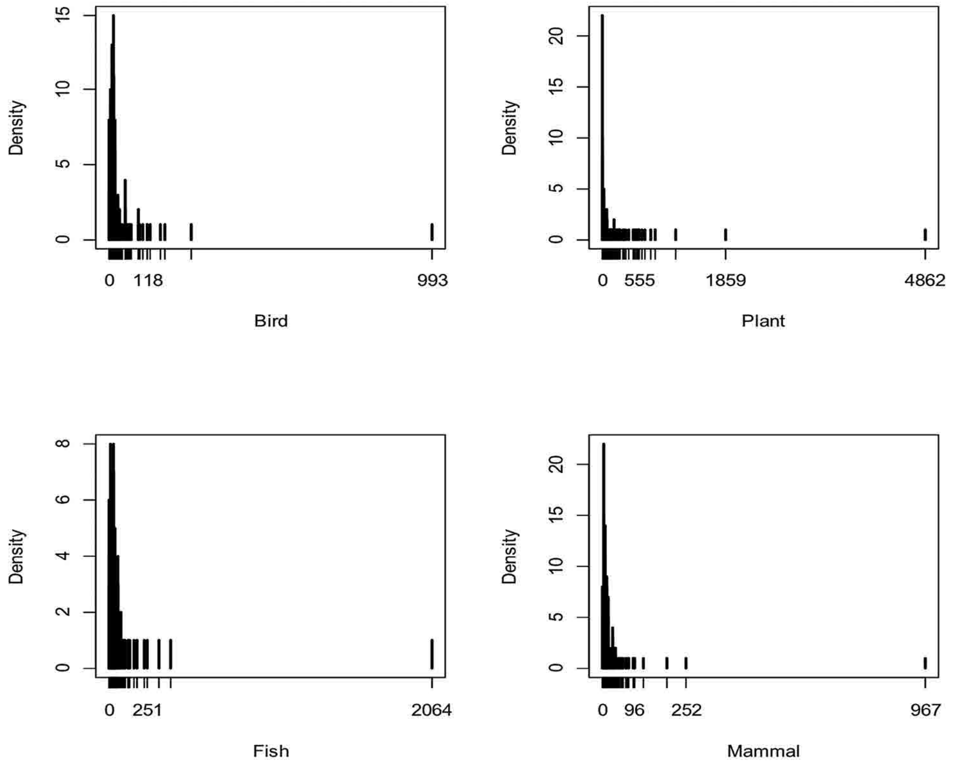
The dependent variable as a proxy variable for biodiversity loss was the count of threatened species (Plant, Mammal, Bird, Fish), measured and registered in statistics at some point in time during 2018.

Independent variables were the countrywide protected areas as a percentage of overall land area (total wide variety) in each country (protect); agricultural production share in GDP (agrgdp); agriculture output of crops produced (crop). According to some prominent authors, the high use of fertilizers, pesticides, and herbicides in agricultural production, followed by speeded-up crop rotation to optimize returns, has resulted in a hostile habitat for many defenseless species, which, in turn, has caused a decline shock of biodiversity in those areas (Pimentel et al., 1992; Wagner & Edwards, 2001; Grashof-Bokdam & van Langevelde, 2004; Billeter et al., 2008). Energy intensity in all economic sectors (tonnes of oil equivalent per million $) (enkgpc) is the next independent variable. Excessive energy intensity may be linked to several disruptions (landscape fragmentations due to infrastructure constructions, power extraction, urban sprawl, etc.) that have a negative effect on biodiversity. At the same time, energy consumption may influence environmental temperature levels, implying a direct impact on biodiversity due to the endangered habitat of vulnerable species (Hutchinson, 1959; Wright, 1983; Allen et al., 2002; Huston, 2003). Meanwhile, intense power consumption can also affect environmental temperature levels, implying a straightforward impact on biodiversity and thereby endangering the habitat of vulnerable species (Hutchinson, 1959; Wright, 1983; Allen et al., 2002; Huston et al., 2003). Our pivotal variable of interest, "arriv ", as a proxy for tourism demand, is measured by the number of international tourist arrivals. Tourism is transport-related activity. Yet, we can't include transport mode choices type of variable (or loosely linked industry or ore exploitation variable) because those data are not available. We believe that biodiversity should be important for the continued improvement of the tourism enterprise, even though there is an apparent lack of knowledge of hyperlinks—positive and negative—between tourism development and biodiversity conservation (Christ et al., 2003). Therefore, we are practically clueless as to whether tourism delivers a positive or negative effect on biodiversity loss. The variable "pop "is the rate of growth of the population; we presume, as in Habibullah et al. (2016), that the better-populated country brings a higher toll on the sustainability of biodiversity.

4. Results

To obtain a quick assessment of the dependent variable, e.g., the number of threatened species (Plant, Mammal, Bird, Fish) along with the world sample, we employ a histogram of the observed count frequencies (Figure 1). The histogram suggests a positive wide variety of zeros (or zero biodiversity loss in some of the countries covered inside the sample set). Of the 176 countries, 22 were assigned to safer plant habitats where we noticed no plant extinction; other species: mammals, birds, and fish (5, 4, and 5, respectively) were, to a lesser degree, threatened across the nations. Furthermore, the data consists of mostly low values and less frequently higher values (illustrated by a long right tail in our histogram). At baseline, the average number of threatened species in 2018 was 107.23 (SD = 378.75, range = 0–4,862); 21.70(SD = 70.07, range = 0–967); 27.06 (SD = 72.53, range = 0–993); 49.62 (SD = 146.01, range = 0–2,064) found within the group for the Plant, Mammal, Bird and Fish variable, respectively. The observed variance to mean ratio is 1,337.75; 226.31; 429.57; 190.83 for the same variable, respectively, clearly indicating overdispersion. After controlling for covariates (protect, agrgdp, crop, enkgpc, arriv, pop) in the Poisson model, the Lagrange multiplier remained highly significant ($\chi 2 = 22{,}824.51$, df = 5, $p < 0.00$), suggesting overdispersion in the case of plants as the dependent variable. Notice that this variable also showed an extremely right-skewed distribution with a spike at zero. The overdispersion is evident in the case of other endangered species (Mammal, Bird, and Fish).

Figure 1
Histogram of biodiversity loss



4.1. Model selection criteria for the fitted model

The model assessments for each of the threatened species are presented in Table 1 using the values from the AIC and BIC as the basis for evaluation.

Table 1
Model selection criteria

	Fitted models			
	Poisson	**NB**	**HP**	**HNB**
Plant				
LL	-15,170.95	-578.34	-14,933.01	-569.63
AIC	30,355.91	1,172.69	29,894.02	**1,169.26**
BIC	30,374.81	1,194.29	29,901.24	1,173.18
Mammal				
LL	-2,140.29	-428.48	-2,130.10	-421.79
AIC	4,294.58	**872.96**	4,288.21	873.57
BIC	4,313.48	894.56	4,356.74	882.32
Bird				
LL	-2,261.54	-464.21	-	-
AIC	4,555.98	**944.42**	-	-
BIC	4,537.07	966.02	-	-
Fish				
LL	-4,155.55	-518.26	-	-
AIC	4,537.07	**966.03**	-	-
BIC	4,555.98	966.03	-	-

Note: Bolded values indicate preferred model.

For the plant species model, both AIC and BIC suggest that the hurdle NB is indistinguishable as the best fit (HNB ≤ HP ≤ NB ≤ Poisson). Here, the hurdle negative binomial model turn out the lowest AIC = 1,169.26 and BIC = 1,173.18 values; while the negative binomial provided a better fit for mammal, bird and fish species (AIC = 872.96, BIC = 894.56; AIC = 944.42, BIC = 966.03 and AIC = 944.42, BIC = 966.03 respectively). We underline here that threatened plants, as we noticed before by counting extinction events in that sort of species across countries, are characterized by a substantially larger number of zeros relative to other species. Therefore, this situation makes modeling count data using the negative binomial model inappropriate in the case of plant species modeling, whereas bird and fish species had an insufficient number of zero outcomes needed in consistent zero-inflating modelings.

Table 2

Vuong non-nested tests result for the threatened species modelling

Dependent variable	Model comparison	Vuong test statistic	p-value	Preferable model
	Poisson vs. NB	-26.25	<0.01	NB
Plant	NB vs. HP	-19.53	<0.02	HP
Plant	HP v. HNB	-15.75	<0.01	**HNB**
Mammal	Poisson vs. NB	-18.83	<0.01	NB
Mammal	NB vs. HP	34.27	<0.03	NB
Mammal	NB vs. HNB	24.17	<0.01	**NB**
Bird	Poisson vs. NB	–61.48	<0.01	**NB**
Fish	Poisson vs. NB	–54.71	<0.01	**NB**

Note: Bolded indicate preferred model.

Since not all of the models were nested with each other, under the null hypothesis that the models were indistinguishable, Vuong tests were used to further compare the above models. The comparison was made between the Poisson and the NB model for bird and fish-threatened species, with a Vuong test of –61.48, and –54.71, of which both statistics result in a negative value with p < 0.01, indicating that the NB model was preferred. After a series of tests and model comparisons (as shown in Table 4.2), where the preferable model was then compared with the next model, HNB was chosen as the best model in the case of plant species. As we see, Voung corrections in targeting for an appropriate model do not generate conflicting outcomes; conclusions according to the best model recognized by previous IC apparatus are the same.

Tables 3 & 4 show the parameter estimates for independent determinants: protect, agrgdp, crop, enkgpc, arriv and pop.

Table 3

The negative binomial regression results

NB	Plant	Mammal	Bird	Fish
intercept	3.81 (9.72)***	2.53 (10.83)***	3.18 (16.19)***	3.18 (15.19)***
protect	0.04 (3.24)**	0.00 (0.24)	0.00 (0.20)	0.00 (0.21)
agrgdp	0.01 (0.02)	0.02 (0.71)**	0.00 (0.31)	0.00 (0.41)
crop	0.01 (0.54)	0.01 (1.45)	0.01 (1.29)	0.01 (1.20)
enkgpc	-0.00 (-4.41)***	-0.00(-2.01)**	-0.00 (-3.06)**	-0.00 (-3.05)**
arriv	0.04 (2.23)**	0.03 (1.99)*	0.03 (2.06)*	0.06 (1.06)
pop	0.03 (3.58)***	0.00 (8.27)***	0.02 (8.65)***	0.01 (8.24)***
AIC	1,172.68	872.96	944.42	944.42
BIC	1,194.29	894.56	966.02	966.02
Log likelihood	-578.34	-428.48	-464.21	-518.26
LR chi2(6)	53.52	103.96	103.82	101.61
Num. obs.	176	176	176	176

Note: Figures in parentheses are t-statistics.
* Statistically significant at 5% level. ** Statistically significant at 1% level. *** Statistically significant at 0.1% level.

Table 3 displays the results of a negative binomial regression model with protect, agrgdp, crop, enkgpc, arriv and pop as the independent variables and the count of Mammal, Bird, and Fish extinction incidents as the dependent variable(s). For the hurdle NB models (Table 4), there are two sets of columns for modeling Plant loss, the first showing the chances that the particular independent variable affected the "structural" zeros (no extinction plant event) and the second showing the model for the "sampling" counts themselves.

The adjudged best model for each of the species was used to predict the determinants of its loss peculiar to each species. For the mammal variable, the share of agrarian production in GDP noticed by the agrgdp variable is a factor driving mammal extinction probability up at a significant level. Our results in this paper, which examines agriculture production intensity in biodiversity issues that tackle only isolated mammal species loss, confirm the finding as with other authors (Pimentel et al., 1992; Wagner & Edwards, 2001; Grashof-Bokdam & van Langevelde, 2004; Billeter et al., 2008, Halkos, 2011). The mammals, birds and fish that reside within habitats in the country where higher energy intensity, noticed by engkgpc, for certain reason prevails, may expect a paradoxically lower rate of extinction. Similarly to our result in the case of birds under threat, the variable energy intensity has a very low negative influence as found in a paper written by Halkos (2011), so our result, in part, validated some old evidence. An increasing level of the population (pop) is the trigger of biodiversity loss according to the next result read from Table 3 at a 1% significant level. That evidence is in line with Habibullah et al. (2016), which gives an assessment that indicates that the greatest impact on biodiversity loss is caused by population growth. Tourism arrivals/increase in-going tourism levels is the factor responsible for the high level of biodiversity loss in the mammal and bird cases; that outcome, it is worth mentioning, with the arriv variable, is significant (at 5%) in our paper. Thus, concerning the tourism-led hypothesis in estimating biodiversity loss, our results here supported the observations and conclusions of previous researchers, which can uncover the significant positive relationship between tourism and biodiversity loss in threatened species of plants, mammals, birds, and fish (Habibullah et al. 2016) at 1% level of significance. The cited authors imply that an increase in tourism is associated with an increase in the number of threatened species (biodiversity loss).

Table 4
The negative binomial hurdle regression results

NB hurdle	Plant
Count model coefficients (truncated negbin with log link)	
intercept	3.65(1.78)
protect	0.04(0.62)
agrgdp	0.01(0.29)
crop	0.00(0.61)
enkgpc	-0.00(0.28)
arriv	0.00(0.14)
pop	0.00(1.34)
Log(theta)	-0.96(0.29)
Zero hurdle model coefficients (binomial with logit link)	
intercept	2.68 (2.28)*
protect	0.23 (0.03)
agrgdp	0.02 (0.28)
crop	0.22 (1.54)
enkgpc	-0.04 (-2.23)*
arriv	0.04 (0.16)
pop	0.00 (0.76)
AIC	1,169.25
Log likelihood	-569.629
Num. obs.	176

Note: Figures in parentheses are t-statistics.
* Statistically significant at 5% level.

The assessment in this paper provides sufficient evidence (see Tables 1 and 2) to firmly support that the plant variable count data, usually rightly skewed with sufficient excess zeros, should be modeled using the zero-augmented models with the negative binomial variant. The NBH model (see Table 4) fails to detect a significant interaction between the dependent plant variable and independent variables, except in the case of the energy intensity variable (enkgpc). The last variable had been assessed at a significant level, at 5%, suggesting that considering all zeros to be "structural" may bias against detecting an effect of including covariates in this cross-sectional sample. We underline that the NB (Table 3) and NBH (Table 4) models yield similar estimates of the included enkgpc determinant, although interaction happened with different species (in the NB regression, outlined species produced evidence at p-value < 5%). Finally, from Tables 3 and 4, we can see that the variable energy intensity has a significant but isolated negative impact on plant extinction, which is similar compared to the other threatened species. Contrary to the theoretical presumption of Hutchinson, 1959; Wright, 1983; Allen et al., 2002; Huston et al., 2003, it seems that a shift to greater power consumption may have a cushion-like effect on biodiversity loss, imposing on the habitat of vulnerable species.

5. Conclusion

One of the most significant manifestations of globalization over the last half-century has been the popularisation of international tourism, which, in our opinion, has brought a great deal of stress on natural habitats and their equilibrium, "traveling humankind" invading the stillness of the earth, air, and water around the world for decades. Humankind living on the pale blue dot, as our planet looks like from above, thanks to the so-called space-shrinking technologies and/or advanced transportation (jets, fast cars, ships, etc.), means we have become more interconnected than ever before. The advantages of a modern style of living are enormous for the average person if they like to travel occasionally once or twice a year in the role of an international tourist, but in the end, nature has to foot the bill for misbehaviors en masse, as we supposed in this paper. Hence, in this paper, we tried to test if international tourist arrivals, along with other forces, had produced a disrupting shock on existing biodiversity, threatening the extinction of plants, mammals, birds, and fish. The conclusion that we brought to light from our assessments is less pessimistic than that of our fellow researching predecessors (Habibullah et al., 2016) because we had found that only mammal and bird species numbers effectively shrink in size if tourism arrivals increase. Additionally, we can add that pieces of evidence had cropped up at a slightly lower significance level than Habibullah et al. (2016). Furthermore, the superior methodology (NB regression vs. OLS regression), which brings us to that conclusion, gives, at the same time, incrementally more weight to our finding. Nevertheless, despite the failure in approaching plant species with HNB regression, we are yet cautious in giving an unambiguous statistical verdict in the matters of plants' probability of extinction linked to tourism arrivals. Namely, the NB regression evidence yet shows that tourism arrivals had a positive impact on plant extinction with a prudent significant level (at 5%), as in Habibullah et al. (2016).

Furthermore, in our study, we find enough evidence that demography plays a key role in biodiversity loss, along with tourism. The disruptive and threatening force of tourism on biodiversity in a global world, triggered by globalization, contributed to poverty alleviation. That transmitted into the rise of the standard of living around the globe. We can follow with the next conjecture—that the positive impact on the procreation of the human race in the spirit of Malthusian demographic theory is effective when the food on the table is abundant. In our era population relentlessly multiplied, thus, making an impact on biodiversity loss.

In this paper, we did not extend our topic to the sustainability questions with deepening philosophical discussions that tackle the role of humankind and the impact that economic growth plays on global biodiversity loss. It has a deep ethical connotation, and the literature has been growing for years on that agenda. It is out of suspicion that anthropocentricity, with its negative driving forces onto biodiversity loss processed in our study, shall not die out very easily; so the question is how to design a unique direction for the improvement of biodiversity, variety of species, and more. Is the conservation of biological habitats of existing threatened species a potential remedy for the global malady caught up in the snapshot of our assessment, in which perpetual tourism growth and the population's pervasive proliferation shall be rendering a risk to biodiversity over the coming years? With conservation, we conceptualize some form of a useful symbiosis of tourist attractions around the world in peril under the pressure of tourism activity.

We foresaw that it will be rather beneficial for tourism agents to create more conservation of the biohabitats in danger around tourism centers. By that, we mean that tourism supply is in urgent need of a variety of free biological species along with the material building blocks of supply (hotels, resorts, restaurants, etc.), all to maintain "business as usual".

A limitation of this paper is that we investigated biodiversity loss only with proposed variables. Because of the unavailability of the transport-linked or industry variables, et cetera, this paper, and we should be self-critical, is not flawless.

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References

Allen, A.P., Brown, J.H. & Gillooly, J.F. (2002). Global biodiversity, biochemical kinetics, and the energetic-equivalence rule. *Science, 297*(5586), 1545-1548. https://doi.org/10.1126/science.1072380

Baum, C.F. (2010). *Models for count data and categorical response data*. Boston College and DIW Berlin, University of Adelaide.

Bhuiyan, M.A., Jabeen, M., Zaman, K., Khan, A., Ahmad, J., & Hishan, S.S. (2018). The impact of climate change and energy resources on biodiversity loss: Evidence from a panel of selected Asian countries. *Renewable energy, 117*, 324-340. https://doi.org/10.1016/j.renene.2017.10.054

Billeter, R., Liira, J., Bailey, D., Bugter, R., Arens, P., Augenstein, I., & Edwards, P.J. (2008). Indicators for biodiversity in agricultural landscapes: A pan-European study. *Journal of Applied Ecology, 45*(1), 141-150. https://doi.org/10.1111/j.1365-2664.2007.01393.x

Brandt, J.S. & Buckley, R.C. (2018). A global systematic review of empirical evidence of ecotourism impacts on forests in biodiversity hotspots. *Current Opinion in Environmental Sustainability, 32*, 112-118. https://doi.org/10.1016/j.cosust.2018.04.004

Cameron, A.C., & Trivedi, P.K. (1998). *Regression analysis of count data*. Cambridge University Press.

Catibog-Sinha, C. (2010). Biodiversity conservation and sustainable tourism: Philippine initiatives. *Journal of Heritage Tourism, 5*(4), 297-309. https://doi.org/10.1080/1743873X.2010.517841

Chipeta, M.G., Ngwira, B.M., Simoonga, C., & Kazembe, L.N. (2014). *Zero adjusted models with applications to analysing helminths count data*. BMC Res Notes.

Christ, C., Hillel, O., Matus, S., & Sweeting, J. (2003). *Tourism and biodiversity: Mapping tourism's global footprint*. Conservation International and UNEP.

Damme, K.V. & Banfield, L. (2011). Past and present human impacts on the biodiversity of Socotra Island (Yemen): Implications for future conservation. *Zoology in the Middle East, 54*(3), 31-88. https://doi.org/10.1080/09397140.2011.10648899

Dinneen, J. (2020, April 3). *COVID-19 disrupts a major year for biodiversity policy and planning*. Mongabay, News and Inspiration From Nature's Frontline. https://news.mongabay.com/2020/04/covid-19-disrupts-a-major-year-for-biodiversity-policy-and-planning

Facemire, C., & Bradshaw, K. (2020). Biodiversity loss, viewed through the lens of mismatched property rights. *International Journal of the Commons, 14*(1), 650–661. http://doi.org/10.5334/ijc.985

Fletcher, R. (2019). Ecotourism after nature: Anthropocene tourism as a new capitalist "fix". *Journal of Sustainable Tourism, 27*(4), 522-535. https://doi.org/10.1080/09669582.2018.1471084

Gössling, S. (1999). Ecotourism: A means to safeguard biodiversity and ecosystem functions? *Ecological Economics, 29*(2), 303-320. https://doi.org/10.1016/S0921-8009(99)00012-9

Grashof-Bokdam, C.J. & van Langevelde, F. (2004). Green veining: Landscape determinants of biodiversity in European agricultural landscapes. *Landscape Ecology, 20*, 417-439. https://doi.org/10.1007/s10980-004-5646-1

Habibullah, M.S., Din, B.H., Chong, C.W., & Radam, A. (2016). Tourism and biodiversity loss: Implications for business sustainability. *Procedia Economics and Finance, 35*, 166-172. http://doi.org/10.1016/S2212-5671(16)00021-6

Halkos, G.E. (2011). Nonparametric modelling of biodiversity: Determinants of threatened species. *Journal of Policy Modeling, 33*(4), 618-635. https://doi.org/10.1016/j.jpolmod.2010.12.005

Hall, C.M. (2010a). Tourism and biodiversity: More significant than climate change? *Journal of Heritage Tourism, 5*(4), 253-266. https://doi.org/10.1080/1743873X.2010.517843

Hall, C.M. (2010b). An island biogeographical approach to island tourism and biodiversity: An exploratory study of the Caribbean and Pacific islands. *Asia Pacific Journal of Tourism Research, 15*(3), 383-399. https://doi.org/10.1080/10941665.2010.503628

Hall, C.M. (2010c). Changing paradigms and global change: From sustainable to steady-state tourism. *Tourism Recreation Research, 35*(2), 131-143. https://doi.org/10.1080/02508281.2010.11081629

Hoogendoorn, G. (2021). Last chance tourism in South Africa: Future research potential? *Tourism: An International Interdisciplinary Journal, 69*(1), 73-82. https://doi.org/10.37741/t.69.1.6

Hoppstadius, F. & Sandell, K. (2018). Tourism – As exploration and demonstration of which sustainable development? The case of a biosphere reserve. *Tourism: An International Interdisciplinary Journal, 66*(2), 161-176. https://hrcak.srce.hr/202745

Horváth, Z., Ptacnik, R., Vad, C.F., & Chase, J.M. (2019). Habitat loss over six decades accelerates regional and local biodiversity loss via changing landscape connectance. *Ecology Letters, 22*(6), 1019-1027. https://doi.org/10.1111/ele.13260

Huston, M. A. (2003). Heat and biodiversity. *Science, 299*(5606), 512-513. https://doi.org/10.1126/science.299.5606.512

Hutchinson, G.E. (1959). Homage to Santa Rosalia or why are there so many kinds of animals. *American Naturalist, 93*(870), 145-159. https://www.jstor.org/stable/2458768

Lam, K.F., Xue, H., & Bun Cheung, Y. (2006). Semiparametric analysis of zero-inflated count data. *Biometrics, 62*, 996-1003. https://doi.org/10.1111/j.1541-0420.2006.00575.x

Malik, M.A.S., Shah, S.A., & Zaman, K. (2016). Tourism in Austria: Biodiversity, environmental sustainability, and growth issues. *Environmental Science and Pollution Research, 23*(23), 24178-24194. https://doi.org/10.1007/s11356-016-7609-x

Mazor, T., Doropoulos, C., Schwarzmueller, F., Gladish, D.W., Kumaran, N., Merkel, K., & Gagic, V. (2018). Global mismatch of policy and research on drivers of biodiversity loss. *Nature Ecology & Evolution, 2*(7), 1071-1074. https://doi.org/10.1038/s41559-018-0563-x

McClendon, M. (1994). *Multiple regression and causal analysis.* F.E. Peacock Publishers.

Newsome, D., & Hughes, M. (2018). The contemporary conservation reserve visitor phenomenon! *Biodiversity and Conservation, 27*(2), 521-529. https://doi.org/10.1007/s10531-017-1435-4

Nyaupane, G.P. & Poudel, S. (2011). Linkages among biodiversity, livelihood, and tourism. *Annals of Tourism Research, 38*(4), 1344-1366. https://doi.org/10.1016/j.annals.2011.03.006

Okello, M.M., & Kiringe, J.W. (2004). Threats to biodiversity and their implications in protected and adjacent dispersal areas of Kenya. *Journal of Sustainable Tourism, 12*(1), 55-69. https://doi.org/10.1080/09669580408667224

Osgood, W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 16*, 21–43. https://doi.org/10.1023/A:1007521427059

Pan, W. (2001). Akaike's information criterion in generalized estimating equations. *Biometrics, 57*(1), 120-125. https://doi.org/10.1111/j.0006-341x.2001.00120.x

Paternoster, R., & Brame, R. (1997). Multiple routes to delinquency? A test of developmental and general theories of crime. *Criminology, 35*(1), 45-84. https://doi.org/10.1111/j.1745-9125.1997.tb00870.x

Pimentel, D., Acquay, H., Biltonen, M., Rice, P., Silva, M., Nelson, J., & D'amore, M. (1992). Environmental and economic costs of pesticide use. *BioScience, 42*(10), 750-760. https://doi.org/10.2307/1311994

Qureshi, M. I., Elashkar, E.E., Shoukry, A.M., Aamir, A., Mahmood, N.H.N., Rasli, A.M., & Zaman, K. (2019). Measuring the ecological footprint of inbound and outbound tourists: Evidence from a panel of 35 countries. *Clean Technologies and Environmental Policy, 21*(10), 1949-1967. https://doi.org/10.1007/s10098-019-01720-1

Reese, R. (2016). *The poisson and negative binomial distributions*. https://stats.stackexchange.com/questions/531119/poisson-gamma-model-for-landslides

Santos Silva, J.M.C., & Covas, F. (2000). A modified hurdle model for completed fertility. *Journal of Population Economics, 13*, 173-188. https://doi.org/10.1007/s001480050132

Scherer, L., Svenning, J.C., Huang, J., Seymour, C.L., Sandel, B., Mueller, N., & van Bodegom, P.M. (2020). Global priorities of environmental issues to combat food insecurity and biodiversity loss. *Science of the Total Environment, 730*, Article 139096. https://doi.org/10.1016/j.scitotenv.2020.139096

Sinclair, M.T., & Stabler, M. (1997). *The economics of tourism*. Routledge.

Sun, Z., Behrens, P., Tukker, A., Bruckner, M., & Scherer, L. (2022). Shared and environmentally just responsibility for global biodiversity loss. *Ecological Economics, 194*, Article 107339. https://doi.org/10.1016/j.ecolecon.2022.107339

The World Bank. (n.d.). *The World Bank indicators*. https://data.worldbank.org/indicator

Tickner, D., Opperman, J.J., Abell, R., Acreman, M., Arthington, A.H., Bunn, S.E., & Young, L. (2020). Bending the curve of global freshwater biodiversity loss: An emergency recovery plan. *BioScience, 70*(4), 330-342. https://doi.org/10.1093/biosci/biaa002

Tovar-Sánchez, A., Sánchez-Quiles, D., & Rodríguez-Romero, A. (2019). Massive coastal tourism influx to the Mediterranean Sea: The environmental risk of sunscreens. *Science of the Total Environment, 656*, 316-321. https://doi.org/10.1016/j.scitotenv.2018.11.399

Van der Duim, R., & Caalders, J. (2002). Biodiversity and tourism: Impacts and interventions. *Annals of Tourism Research, 29*(3), 743-761. https://doi.org/10.1016/S0160-7383(01)00087-1

Vrieze, S.I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological methods, 17*(2), 228. https://doi.org/10.1037/a0027127

Vuong, Q.H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica, 57*(2), 307-333. https://doi.org/10.2307/1912557

Wagner, H.H., & Edwards, P.J. (2001). Quantifying habitat specificity to assess the contribution of a patch to species richness at a landscape scale. *Landscape Ecology, 16*(2), 121-131. https://doi.org/10.1023/A:1011118007670

Winkelman, R., & Zimmermann, K.F. (1995). Recent developments in count data modelling: Theory and application. *Journal of Economic Surveys, 9*(1), 1-24. https://doi.org/10.1111/j.1467-6419.1995.tb00108.x

Wolf-Watz, D. (2014). Traveling for nature? On the paradox of environmental awareness and travel for nature experiences. *Tourism: An International Interdisciplinary Journal, 62*(1), 5-18. https://hrcak.srce.hr/120556

World Tourism Organization. (2017). *Sustained growth in international tourism despite challenges*. https://www.unwto.org/archive/global/press-release/2017-01-17/sustained-growth-international-tourism-despite-challenges

World Tourism Organization. (2020). *International tourism growth continues to outpace the global economy*. https://www.unwto.org/international-tourism-growth-continues-to-outpace-the-economy

Wright, D.H. (1983). Species-energy theory: an extension of species area theory. *Oikos, 41*(3), 496-506. https://doi.org/10.2307/3544109

Yassin, J., Aralas, S., & Basa, D.E. (2020). Tourism density effect on environmental performance index: Evidence in ASEAN countries. *Applied Environmental Research, 43*(1), 90-101. https://doi.org/10.35762/AER.2021.43.1.7

Yesilova, A., Kaydan, M.B., & Yilmaz, K. (2010). Modeling insect-egg data with excess zeros using zero-inflated regression models. *Hacettepe Journal of Mathematics and Statistics, 39*(2), 273-282. http://www.hjms.hacettepe.edu.tr/uploads/c879f14e-8c0d-4f30-8bfa-e28658a8fe0b.pdf

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