Species Imperilment and Spatial Patterns of Development in the United States

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Abstract: Conservation biologists and others hypothesize that humankind’s “ecological footprint” is affected not only by the sheer intensity of human activity but also by its spatial arrangement. We used a multivariate statistical model and state-level data to evaluate correlations between species imperilment and the level and spatial distribution of human settlement and infrastructure development in the United States. The level of human activity—measured by the number of people and households, incidence of roads, and intensity of nighttime lights—was significantly correlated with the ecological imperilment of species. Our regression models consistently showed that a 1% increase in the level of human activity across the United States was associated with about a 0.25% increase in the proportion of plant and animal species considered at risk of extinction by The Nature Conservancy. The distribution of human activity did not affect species imperilment. Our results point to rising levels of human activity—and not some particular (e.g., sprawling) distribution of human activity—as the most relevant anthropogenic factor explaining biodiversity loss in the United States.

Key Words: ecological footprint, endangered species, human activity

Introduction

Several recent studies quantify and rank the causes of species endangerment (e.g., Dobson et al. 1997; Wilcove et al. 1998; Czech et al. 2000; McKinney 2002a). This research shows that human activities (e.g., urbanization, agriculture, mining, and road building) rather than natural circumstances (e.g., genetic problems, disease) threaten the survival of nonhuman species most. Although this information helps conservation scientists know which
human activities most adversely affect biodiversity, it does not reveal how many species may be typically lost (or spared) given specific changes in current human activity levels. For example, Czech et al. (2000) found that “road presence, construction, and maintenance” endangers 94 species in the United States (thirteenth leading threat). Policy makers and others may wonder how many more (or fewer) species would be imperiled if road presence were increased (or decreased) by a specific amount. Existing studies do an excellent job showing us the direction of change; for example, Blair (1996) shows that increasingly intense development is inversely related to total and native bird species diversity. What we lack is information about the sensitivity or responsiveness of species richness to changes in human activity levels (i.e., how much—direction and magnitude—changes in human activity affect species diversity).

A related question dealing with the distribution—rather than the level—of human activity also needs additional study. A link between species imperilment and the distribution of human activity is often conjectured, but to our knowledge empirical support for such relationships is lacking. In the forestry literature, scientists speculate that intensively managed timber, as a human activity, reduces the imperative to cut from “natural” forests, leaving more forest land intact and undisturbed (Wallinger 1993; South 1999; Bowyer 2001). The idea is that species imperilment may be reduced if, for a given harvest level, timber production is unequally distributed in spatial terms with production concentrated in part on ecologically homogenous tree plantations and diffuse in part with some relatively pristine forest areas. This idea that an unequal distribution of human activity has biodiversity benefits also underlies arguments for smart growth (e.g., Babbitt 1999; Filion 2003) and the establishment of protected areas (e.g., Redford & Sanderson 2000). In our analysis, we examined empirically these two questions, namely how levels and distributions of human activity affect species richness and imperilment.

**Methods**

We used a multivariate statistical model and state-level data to evaluate correlations between species imperilment and the level and spatial distribution of human settlement and infrastructure development in the United States. We modeled species imperilment (number of at-risk species) in an area as a function of species richness (number of different species), levels of endemism (number of species found only within that area and nowhere else), geographic extent, and level and distribution of human activity. Our general functional form was

\[
\text{number of imperiled species} = f\left(\text{species richness, endemic species number of area level of concentration human of human activity activity}\right)
\] (1)

Because the number of imperiled species is most likely related to species richness (Wilson 1988), we modeled species imperilment and the level of endemism as fractions of all known species. This simplified model expresses species imperilment and the number of endemic species as proportions of total species:

\[
\text{percent imperiled species} = f\left(\text{percent endemic species of area level of concentration human of human activity activity}\right)
\] (2)

This revised model accounts for differences in species richness implicitly and has the added advantage of increasing statistical degrees of freedom.

The expected signs are given above each variable. The percentage of imperiled species is expected to increase as the percentage of endemic species increases or as the level of human activity increases (McKinney 2001, 2002b). Holding the level of human activity constant, the percentage of imperiled species and the unit area should be negatively correlated because increases in area effectively decrease the density of human activity. Those that advocate spatial management of human populations to reduce species imperilment implicitly assume that the proportion of imperiled species and concentration of human activity are negatively correlated. In other words, the level of species imperilment should decrease as the concentration of human activity increases, holding the area under consideration constant.

Limited sub-state-level data on species richness constrained our unit of analysis to U.S. states. We excluded Hawaii because an alternative mix of human and environmental factors is thought to drive species imperilment on islands (Czech et al. 2000). NatureServe provides state tallies of “at-risk” species with conservation rankings of extinct, imperiled, or vulnerable (Stein 2002). Our data for imperiled species included only those species in the latter two categories.

Drawing from existing literature, we identified four unique ways to measure the level of human activity within states: (1) number of people, (2) number of households, (3) street-side mileage of roads, and (4) brightness of nighttime lights. Data for the first three measures are available from the 2000 U.S. census. Data for the brightness of nighttime lights are available at http://www.ngdc.noaa.gov (stable nighttime lights, 2000).

No single measure of human activity seemed most appropriate; each measure has its advocates. Keilman (2005), Liu et al. (2005), and others argue that the number of households more accurately reflects human impacts than population. Holding population constant, a higher number of households implies greater demand for housing-related resources than a smaller number of households. In turn, this implies that the former draws more land and other raw materials into the production of
housing and away from other uses such as wildlife habitat. More people, by contrast, may have a proportionately less significant impact on resource use if the number of households remains constant. Roads are also thought to increase species imperilment by fragmenting habitat, restricting animal migration, and serving as conduits for invasive species (Forman 2000; Trombulak & Frissell 2000; Gelbard & Belnap 2003). Nighttime lights directly affect species too, most notably migratory birds and sea turtles (Peters & Verhoeven 1994; Fedun 1995). More important, perhaps, the extent and brightness of nocturnal lighting correlate highly with numerous indicators of human activity such as city size, economic output, and energy use (Elvidge et al. 1997a, 1997b). The brightness of nighttime lights thus serves as a proxy for a wide range of human activities thought to affect species imperilment, either directly or indirectly.

We used the Gini coefficient of inequality (GC) to measure the distribution of human activity across states. The coefficient is based on the Lorenz curve, a cumulative frequency curve that compares skewness in the distribution of a specific variable (e.g., human activity) against a uniform distribution. We calculated coefficients for each of the four unique measures of human activity as follows:

$$GC = 1.0 - \sum_{i=1}^{N} (X_i - X_{i-1})(Y_i + Y_{i-1}),$$

where $X_i$ is the cumulative percentage of land area and $Y_i$ is the cumulative percentage of total human activity (e.g., proportion of total population). To calculate $X_i$ and $Y_i$, each state must be divisible into geographic subunits, where the size of subunits corresponds to the relative accuracy of the resulting GC measure; smaller (i.e., more numerous) subunits yield more accurate GC estimates. In the case of people, households, and roads, subunits were based on census tract data. To control for variation in size of the census tracts, we normalized census-tract areas by calculating the average amount of human activity per unit area (e.g., average population per square kilometer). Light distribution was evaluated using subunits of 1 km². As a measure of concentration, we used the Gini coefficient, which has desirable statistical properties (mean and size independence, symmetry, and Pigou-Dalton transfer sensitivity) and is one of the most accepted and widely used such measures available (Hart 1971).

Gini coefficient values range from 0 to 1 (higher values corresponded to greater concentration). A perfectly uniform distribution of human activity across a state would have a GC value of 0; conversely, if the entire population of a state were concentrated in a single location, the GC value would be 1. Thus, higher GC values signify greater degrees of concentration. In our sample of population Gini coefficients, Vermont (0.58) and Nevada (0.96) represented the two extremes (Table 1). Vermont’s population was distributed much more evenly across that state than in Nevada, where nearly half the population is concentrated in only two metropolitan areas (Las Vegas and Reno).

With four unique and defensible ways of measuring both the level and distribution of human activity at the state level, we faced three options: (1) combine the four measures in some way to create a single composite value...
for each variable, (2) include all four measures of each variable in one model, or (3) estimate four different regressions, each with its own unique pair of values. Option one is inappropriate without any a priori guidance about how to construct such composite values (e.g., How should the measures be weighted?). Option two raises theoretical concerns about irrelevant (i.e., redundant) variables and empirical concerns about collinearity and degrees of freedom. Option three may raise questions about model specification (e.g., Which is best?), but it reveals useful information about the robustness of our general model. Simple correlations provide insights into robustness. Here, correlations ranged from 0.61 between roads and households to 0.99 between people and households.

We used ordinary least-squares regression to estimate four distinct double-log form specifications of the basic model (Eq. 2). Following option three, each specification included only one of the four different measures of human activity and its related measure of concentration. We also included geographic dummy variables for states in the West, South, and Northeast. Midwestern states were the omitted control group.

**Results**

As expected, the percentage of endemic species and the level of human activity were strong, positive predictors of species imperilment in all four specifications of the basic model (Table 2). The level of human activity was also positively related to species imperilment in all four models. A greater proportion of species is likely to be at risk if the number of people or households, the incidence of roads, or the intensity of nighttime lights increases. Because the basic model was estimated in double-log form, coefficient estimates may be interpreted as elasticities. For example, Table 2 shows that the human activity coefficient estimate for the people model is 0.218. This number implies that the proportion of at-risk species would increase by 0.218% for every 1% increase in the number of people across states, *ceteris paribus*. Likewise, a 1% increase in the number of households, incidence of roads, or the intensity of nighttime lights would result in a 0.210%, 0.204%, and a 0.278% increase in the proportion of at-risk species, respectively. Across all four specifications, a 1% increase in either the level of human activity or the proportion of endemic species was associated with a nearly 0.25% increase in the percentage of imperiled species.

The distribution of human activity (whether diffuse or concentrated) had no meaningful (i.e., statistically zero) impact on species imperilment at the state level. Species imperilment was not significantly related to any of the four different measures defining the concentration of human activity. For a given number of people or households, a set length of roads, or a fixed intensity of nighttime lights, the proportion of species in a state that is at risk of extinction appeared unaffected by how such human activity was distributed within that state.

Table 2. Regression results estimating the proportion of species by U.S. state that are at risk of extinction.

<table>
<thead>
<tr>
<th>Variable</th>
<th>People</th>
<th>Households</th>
<th>Roads</th>
<th>Lights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>−0.926 SE 0.401 p 0.026</td>
<td>−0.709 SE 0.395 p 0.080</td>
<td>−0.108 SE 0.427 p 0.801</td>
<td>−0.352 SE 0.338 p 0.304</td>
</tr>
<tr>
<td>Endemic species (%)</td>
<td>0.206 SE 0.041 p 0.000</td>
<td>0.214 SE 0.042 p 0.000</td>
<td>0.263 SE 0.049 p 0.000</td>
<td>0.217 SE 0.043 p 0.000</td>
</tr>
<tr>
<td>Area (of state)</td>
<td>0.018 SE 0.048 p 0.712</td>
<td>0.007 SE 0.048 p 0.884</td>
<td>−0.090 SE 0.071 p 0.214</td>
<td>−0.114 SE 0.083 p 0.178</td>
</tr>
<tr>
<td>Human activity</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>people</td>
<td>0.218 SE 0.041 p 0.000</td>
<td>0.210 SE 0.044 p 0.000</td>
<td>0.204 SE 0.087 p 0.024</td>
<td>0.278 SE 0.073 p 0.000</td>
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<tr>
<td>households</td>
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<td>roads</td>
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<td>lights</td>
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<td>Human distribution</td>
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<tr>
<td>people</td>
<td>−0.686 SE 0.443 p 0.129</td>
<td>−0.575 SE 0.469 p 0.227</td>
<td>0.079 SE 0.163 p 0.628</td>
<td>0.520 SE 0.550 p 0.350</td>
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<tr>
<td>households</td>
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<td>lights</td>
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<tr>
<td>West</td>
<td>0.336 SE 0.073 p 0.000</td>
<td>0.336 SE 0.077 p 0.001</td>
<td>0.201 SE 0.080 p 0.016</td>
<td>0.343 SE 0.081 p 0.000</td>
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<tr>
<td>South</td>
<td>0.186 SE 0.053 p 0.001</td>
<td>0.192 SE 0.055 p 0.000</td>
<td>0.184 SE 0.061 p 0.004</td>
<td>0.222 SE 0.054 p 0.000</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.023 SE 0.054 p 0.673</td>
<td>0.022 SE 0.056 p 0.700</td>
<td>0.044 SE 0.070 p 0.529</td>
<td>0.070 SE 0.061 p 0.258</td>
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<tr>
<td>Model R²</td>
<td>2.901 SE 0.894 p 0.853</td>
<td>0.853 SE 0.889</td>
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</tbody>
</table>

*aModel expressed in double-log form so that coefficient estimates may be interpreted as elasticities. For example, the human activity coefficient estimate for the people model is 0.218, meaning that a 1% increase in the number of people across states increases the proportion of at-risk species (the dependent variable) by 0.218%.

*bHuman distribution reflects how concentrated or diffuse (as measured by a Gini coefficient calculation) human activity is within U.S. states.

*cStates in these geographic regions listed in a footnote to Table 1.
Discussion

In general, our results point to rising levels of human activity—and not some particular (e.g., sprawling) distribution of human activity—as the most relevant anthropogenic factor explaining biodiversity loss in the United States. Our finding that the level of human activity is positively related to species imperilment reinforces and extends the findings in a number of existing studies. For instance, Liu et al. (2003) and Keilman (2003) note that the rapid increase in household numbers, often manifested as urban sprawl, poses serious challenges to biodiversity conservation. Our analysis quantifies this threat and provides empirical estimates of its impact on one important measure of biodiversity. The population of California, for example, is expected to increase by some 46% by 2025 (Campbell 1997); our model predicts that this population increase will add 185 species to that state’s list of imperiled species, an increase of nearly 10%.

We were surprised to find that patterns of human infrastructure development were statistically unrelated to species imperilment. This result may be explained, in part, by considering that spatially concentrated human populations still impose far-reaching ecological impacts on the environment. If species imperilment and patterns of infrastructure development are unrelated, we wonder whether efforts to expand nature preserves or manage spatial development patterns (e.g., smart-growth planning) would yield aggregate biodiversity benefits. Our results are arguably insufficient to answer this kind of question. Most biodiversity and smart-growth planning takes place at the city or county level, whereas our analysis was based on state-level data. When species data (specifically, species richness data) are available at more refined scales, our models should provide more defensible critiques of the biodiversity benefits of smart-growth planning efforts.

That the distribution of human activity had no significant effect generally in our state-level models does not mean such factors do not matter (particularly at smaller scales). It means only that we could find no good evidence to support any other conclusion. Independent variables (e.g., our distribution parameters) may be statistically not significant if they are highly correlated with other independent variables. The Gini coefficient variables were correlated most highly with area (0.536 in the case of the GC variable for people). Although individual interpretations may vary, correlations of this magnitude are not typically viewed as statistically problematic. This finding of not significant similarity may result from insufficient variation in the distribution variables. In other words, the more similarly human activity is spatially distributed across states, the less likely the Gini values in our models will be significant statistically. Although the range (Table 1) for each GC variable was relatively high (43% average variation), coefficients of variation across these variables were relatively low (between 0.02 and 0.05). This observation might be grounds for concern were it not also true that the two most highly significant GC variables, for people ($p = 0.13$) and households ($p = 0.23$), also had the two lowest coefficients of variation (0.0191 and 0.0196, respectively).

Beyond these two possible statistical concerns, two more general cautions apply. First, inferring causation (e.g., increasing population causes increased species imperilment) from statistical correlation is fraught with problematic assumptions and should be viewed critically. Second, although we sought to use the best available data in the most fruitful ways, our findings should be regarded as preliminary and too abbreviated for policy prescriptions.

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Literature Cited