THE IMPACTS OF HUMAN SPATIAL CONCENTRATION,

ECONOMIC FREEDOM, AND CORRUPTION

ON SPECIES IMPERILMENT

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THE IMPACTS OF HUMAN SPATIAL CONCENTRATION,

ECONOMIC FREEDOM, AND CORRUPTION

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Ram Pandit

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Ram Pandit

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VITA

Ram Pandit, son of Biswamitra Pandit and Padmawati Pandit, was born on September 19, 1967, in Sange village of Tanahun District, Nepal. He graduated from Nirmal High School, Damauli, Tanahun, in 1984. He attended the Institute of Forestry, Tribhuvan University, Nepal, for two years and graduated with an Intermediate Science degree in Forestry in 1988. He worked as a Forest Ranger for 3 years at Lumle Agricultural Research Center's Forestry/Pasture Section before returning to the Institute for his Bachelor's degree in 1991. He received his Bachelor of Science degree in Forestry from the Institute of Forestry in 1994 and returned to Lumle Agricultural Research Center and worked until July 1998 as an Agro-Ecological Research Site Coordinator. In the meantime, he joined the Forest Service of the Government of Nepal as an Assistant Forest Officer and worked for 3 years in different districts before starting higher studies in the U.S. He received a Fulbright Scholarship in 2001 and studied at the SUNY, College of Environmental Science and Forestry, Syracuse, NY for his M.S. degree in Forest Resource Management. He graduated from ESF in summer 2003 and enrolled at Auburn University to pursue a Ph.D. in Forest Economics in fall 2003. Along with his Ph.D. program, he received M.S. degrees in Probability and Statistics (Spring 2006), and in Economics (Fall 2006) from Auburn University. He married Sabina Mishra, daughter of Ishwori Mishra and late Toya Nath Mishra, on December 14, 1997. He has one daughter – Simone, 8 and one son – Seamus, 6.

DISSERTATION ABSTRACT

THE IMPACTS OF HUMAN SPATIAL CONCENTRATION,

ECONOMIC FREEDOM, AND CORRUPTION

ON SPECIES IMPERILMENT

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Advocates of certain public policies believe that alternative spatial distributions of a fixed-size human population have different environmental consequences. Specifically, a more concentrated human population has a smaller 'ecological footprint' and thereby generates lesser environmental harm *in the aggregate*, as compared to a scattered distribution of the same size population. Similarly, the economic freedom and corruption literature links these institutional and human behaviors to environmental outcomes through economic growth. In general, economic freedom (corruption) increases (decreases) economic well-being in a country and the increased (decreased) economic well-being has a positive (negative) effect on environmental outcomes in that country. Considering species imperilment as an aggregate form of the environmental outcome, this

dissertation aims to explore the empirical linkages among spatial concentration of a fixed size human population, economic freedom, and corruption with species imperilment at the country level for five taxa: birds, mammals, reptiles, amphibians, and vascular plants.

International data on threatened species, endemic species, population density, a Gini coefficient index of human concentration, per capita income, economic freedom, and corruption for 173 countries are analyzed with econometric techniques that permit adjustment for spatial autocorrelation across countries using four alternative spatial adjacency specifications: simple, 2nd order, centroid distance, and shared border length.

Results indicate that human population concentration is associated with reduced imperilment among amphibians and vascular plants but *increased* imperilment among mammals, reptiles, and birds. Spatial autocorrelation across countries is found in all five taxa examined, for all spatial dependency specifications, suggesting that the factors that influence species imperilment extend beyond arbitrary political boundaries. Among four spatial adjacency specifications, a simple adjacency measure is found superior to a measure of the percentage of shared border, for all five taxa. The results of introducing both general and specific controls for spatial autocorrelation revealed that the specific variable based spatial controls can substantially change not only the size and statistical significance of the general spatial autocorrelation term but also the size, sign, and/or statistical significance of the explanatory variables.

Furthermore, the results indicate that economic freedom has significant impacts on the imperilment of birds, mammals, and reptiles, whereas corruption only impacts the imperilment of birds. In general, more economic freedom and less corruption beyond a certain threshold reduce species imperilment in a country.

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CHAPTER 1

INTRODUCTION

Biodiversity loss is one of the most serious ecological problems in today's world. Species imperilment is generally considered to be an indicator of biodiversity loss and refers to the ecological viability of the species population. A conservative estimate of the 2004 IUCN Red List suggests that of the world's 1.9 million described species, 15,589 species are threatened with extinction (Baillie, Hilton-Taylor, and Stuart 2004). Worldwide, at the taxonomic level, 12% of birds, 23% of mammals, 32% of amphibians, 42% of turtles and tortoises, 25% of conifers, and 52% of cycads are identified as threatened with extinction (Baillie, Hilton-Taylor, and Stuart 2004). Succession, endemism, climate, and geography are some natural factors associated with species imperilment.

Moreover, human-induced factors are largely blamed for species imperilment and extinction (Soule 1991; Forester and Machlis 1996; Baillie, Hilton-Taylor, and Stuart 2004). Major human-induced factors include deforestation, habitat fragmentation, over-exploitation of populations (e.g. hunting, fishing), introduction of invasive species and diseases, pollution, climate change (Soule 1991; Berger and Berger 2001; Sanderson et al. 2002), urbanization (McKinney 2002a; Riley et al. 2003; Turner, Nakamura, and Dinetti 2004), and economic activities (Naidoo and Adamowicz 2001; Asafu-Adjaye 2003; McPherson and Nieswiadomy 2005). However, increased human population

size, as measured by population density, is considered the most important driver of this phenomenon (Wilson 1988; Kohn 1999; Cincotta and Engelman 2000; Liu et al. 2003; Naves et al. 2003).

Even though the ecological impact of alternative spatial distributions of a fixed-size human population has barely been acknowledged, much less investigated thoroughly, both public agencies and non-governmental organizations have formulated and advocated policies to control the spatial distribution of humans. For example, advocates of the Smart-Growth principle of Compact Building Design argue that there are ecological advantages, in the aggregate, to managing human distribution patterns in a way that reduces the footprint of new construction (Ewing, Pendall, and Chen 2002). However, in terms of resource requirements, it seems reasonable to suggest that a fixed-size human population requires the same amount of productive resources regardless of spatial distribution. Consequently, having the population located physically in one place does not necessarily imply that the rest of the area is untouched. At a minimum, empirical support for the claimed ecological benefits of compact building design has not been well established in the scientific literature.

In the literature, the empirical relationship between economic freedom and /or corruption and ecological outcomes in a country has been suggested implicitly via economic growth or well-being. Numerous studies have documented the direct link between economic freedom and economic well-being (Islam 1996; Berggren 2003; Cole 2003; Vega-Gordillo and Alvarez-Arce 2003; Gwartney, Holcombe, and Lawson 2004; Doucouliagos 2005) and between corruption and economic well-being (Friedman et al. 2000; Li, Xu, and Zou 2000; Mo 2001; Gyimah-Brempong 2002; Mauro 2004) at a

country level of analysis. Similarly, a direct link between economic well-being and environmental outcomes also has been frequently studied (Grossman and Krueger 1995; Asafu-Adjaye 2003). These latter studies suggest a potential Environmental Kuznets Curve (EKC) relationship between economic well-being and specific forms of environmental degradation, for example pollution (Selden and Song 1994) and deforestation (Stern, Common, and Barbier 1996). Considering loss of species as a form of environmental degradation, the EKC relationship has been suggested for threatened or imperiled species (Naidoo and Adamowicz 2001; McPherson and Nieswiadomy 2005). Thus, an implicit theoretical link between economic freedom and/or corruption and species imperilment via economic well-being can be extended based on existing literature. However, a potential direct link between them and its empirical validity remains an investigative issue in the literature.

Therefore, this dissertation explores the empirical linkage between species imperilment and the spatial concentration of humans, economic freedom, and corruption at the country level for five taxa: breeding birds, mammals, reptiles, amphibians, and vascular plants. More specifically, it focuses on the following two specific objectives:

- to test the empirical validity of the assumption of reduced species imperilment by managing human distribution at the aggregate as well as the taxa level,

- to explore the direct empirical links of economic freedom and corruption to species imperilment across countries by taxa groups.

However, comparable data on species imperilment are available only at a country by country level, but the political boundaries of countries, the limiting factor for the data; do not necessarily delimit the factors of species imperilment among countries. In other

words, spillover effects of social, ecological, and economic factors across political

boundaries are common, due to mutual spatial dependency between countries. This

mutual dependency raises an analytical concern, often referred as spatial autocorrelation,

in cross country studies including species imperilment. Spatial dependency is inherent in

all geographic data, as argued by Tobler's first law of geography (1970), which states,

"Everything is related to everything else, but near things are more related than distant

things." In the context of species imperilment study, spatial autocorrelation is not only

relevant but also important in the following three respects: (1) the nature of dependency,

if it exists – spatial lag or error; (2) the optimal type of adjacency measure – 1st order

adjacency, 2nd or higher order adjacency, shared border length, or centroid distance

between countries; and (3) the role of specific independent variables on dependency

relationship beyond conventional spatial lag (dependent variable based) or spatial error

(error based) dependencies. Thus, the issue of spatial autocorrelation in species

imperilment models becomes a methodological focus in this study. Research on spatial

dependency based empirical analysis of species imperilment has just begun. McPherson

and Nieswiadomy (2005) have advanced the work in this direction. However, since their

work is confined to the spatial lag dependency based on shared border length measure

only, a full understanding of alternative spatial dependency measures and independent

variables based dependency relationships is crucially lacking in the literature.

Species imperilment is the resultant expression of many factors that occur either

naturally or by human actions (Wilson 1988). Thus, it is believed that species

imperilment is a comprehensive *aggregate* indicator of ecological condition in a country,

since deforestation, climatic variations, land use patterns, and urbanization that affect

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species and their ecological viability can well be represented in a single measure. For the purpose of this dissertation, percent threatened or imperiled species among five taxa groups is considered as the representative form of ecological outcomes in a country and is the key variable of study. Consistent with IUCN classification, imperiled or threatened species is categorized as the sum total of critically endangered, endangered, and vulnerable species in a country (Baillie, Hilton-Taylor, and Stuart 2004). Previous studies have used the percentage of threatened species (McPherson and Nieswiadomy 2005), number of threatened species (Naidoo and Adamowicz 2001), and the density of threatened species (Forester and Machlis 1996) as measures of species imperilment. In this study, percent imperiled species is considered as the dependent variable in species imperilment models, since percentage is the proportionate representation of total species of specific taxa in a country and can be a comparable measure among countries of different size.

Considering each country as a unit of analysis, international data produced or compiled by World Conservation Union, World Resources Institute, United Nations, International Monetary Fund, Oak Ridge National Laboratory, the Heritage Foundation, and Transparency International are used in this study. The explanatory variables include percent endemic species, human population density, a Gini coefficient index of human concentration, economic well-being as measured by per capita GDP, an economic freedom index, a corruption index, and a dummy variable to signify the bio-physical nature of countries. The impacts of ecological factors, human distribution, activities, and behaviors on imperilment of species across countries are analyzed to answer the questions imbedded in the specific objectives above.

Endemic species reflect a large number of ecological factors since endemism is the manifestation of ecological uniqueness, including temperature, precipitation, soil, and other biotic and abiotic factors. A new metric of human spatial distribution, as represented by the Gini coefficient for population concentration, is introduced along with population density to analyze the empirical validity of assumptions advocated by smart-growth adherents. In a broader sense, economic well-being represents human activities, and economic freedom and corruption represent human behaviors for this study. Countries are divided into two groups, mainland and island, to represent the biophysical differences between them.

Data on model variables for 173 countries are analyzed with an econometric technique that permits adjustment for spatial autocorrelation in GEODA and the robust regression technique that controls for the influence of outlying observations in SAS. The imperiled and endemic species data across five taxa groups are combined for aggregate analysis. The following hypotheses corresponding to each set of objectives are tested during the analysis:

- Following the claim made by "Smart-growth principle of compact building design adherents," it is hypothesized that species imperilment is related to human concentration patterns both in the aggregate and for specific taxa across the countries. Specifically, the more uniform the human distribution in a country is, the more threatened or imperiled the species living within that country are, and vice versa.

- It is further hypothesized that economic freedom and corruption in a country have respectively an inverse and a direct relationship with species imperilment in that

country. The more economic freedom there is in a country, the less imperiled are the species in that country, and vice versa. Similarly, the more corrupt the country is, the more imperiled the species in that country are, and vice versa.

This dissertation is developed in a manuscript format with a connecting link of research question and analytical approach between the chapters. This is the first and introductory chapter. The second chapter presents a collective review of literature that sets the research questions in perspective. The third chapter discusses the idea of smart-growth and assumed ecological benefits of concentrating humans and presents empirical results of species imperilment both at aggregate and taxa level analyses. The fourth chapter explores the issue of spatial autocorrelation in species imperilment models and presents the spatial analyses for all four adjacency measures by taxa. It further expands the spatial analysis, incorporating general and specific variable-based spatial lags into the models to gain more insights into the role of specific variables on species imperilment across countries. The fifth chapter constructs a linkage between economic freedom and corruption with species imperilment. The sixth chapter summarizes the main findings.

It is worth mentioning at the onset that given the aggregate nature of the data available at the country level, the specific questions based on ecological variations or any other types within a country are not addressed in this dissertation. A note of caution is warranted if we want to interpret the results within a country's context.

CHAPTER 2

LITERATURE REVIEW

2.1 Human Population Size, Concentration, Activities, and Species Imperilment

The deliberate manipulation of habitat by human beings poses a different picture on the natural processes of succession and coexistence of all species (Odum 1971). This raises a direct question about impacts of human population and associated activities on other species who share common resources such as land, water, air, and forests with humans. Both in theoretical and empirical studies, human population and activities are often cited as prime causes of biodiversity loss (Forester and Machlis 1996; Kohn 1999; Cincotta and Engelman 2000; Berger and Berger 2001; Sanderson et al. 2002; Liu et al. 2003; Naves et al. 2003).

Threatened or imperiled species have been considered an indicator of biodiversity loss in earlier studies. Specifically, species density (Asafu-Adjaye 2003), number of threatened species (Kerr and Currie 1995; Forester and Machlis 1996; Naidoo and Adamowicz 2001), and percent threatened species (Forester and Machlis 1996; McPherson and Nieswiadomy 2005) were used at country level studies.

Even though ultimate causes of biodiversity loss vis. a vis. species imperilment are complex and vary by social context (Soule 1991), the causal factors and consequences of such losses have been well documented, and human population growth expressed in the form of density has been identified as one of the dominating factors in the literature

(Wilson 1988; Meffe, Ehrlich, and Ehrenfeld 1993). Notable human activities for adverse ecological outcomes that impact species imperilment identified by earlier studies include deforestation (Rudel 1989), mining and intensive forestry (Saunders, Hobbs, and Margules 1991), introduction of invasive species (Czech and Krausman 1999), urbanization and urban sprawl (McKinney 2002a), and economic development (James 1994). With an ever-increasing human population, as Watson (2004) argued, there is a need to look at social structures, consumption pattern, commodity intensive development, and the social and historical causes of extreme poverty while considering underlying causes of ecological degradation. In the same tone, Machlis (1992) emphasized the need to understand social structures and behaviors in order to understand species imperilment since the causes of habitat destruction are complex and ultimately linked with demographic patterns, national histories, land tenure rules, the distribution of wealth, worldwide trends toward industrialization, increased per capita energy consumption, and economic interdependence among countries.

There is an emerging literature that links urbanization with species diversity. Generally, urbanization is found to depress biodiversity due to habitat loss, particularly for native species (McKinney 2002a; Turner, Nakamura, and Dinetti 2004). However, other studies have shown that the number of native species decreases while the number of non-native species increases in suburban areas due to the invasion of non-native species, particularly birds and butterflies (Blair 1996). The study on human footprint, the map of human influence on nature that expresses the sum total of human influence stretched across the land surface in a continuum, has also been considered a measure of human impacts on species. This was mapped by using proxies for human influences, such as

population density, land transformation, accessibility, and electrical power infrastructure. In their human footprint mapping study, Sanderson et al. (2002) found that 83% of the land's surface and 98% of the area where it is possible to grow rice, wheat, or maize are directly influenced by human beings. This implies that human activities impact species imperilment, either positively or negatively. The literature has established and documented that human population level or density significantly impacts species imperilment.

However, empirical studies based on alternative measures of human presence, such as the Gini coefficient for human concentration or human settlement patterns and species imperilment, are not widely available even though public policies have been developed to minimize human footprints based on the assumptions that certain forms of human settlement patterns are more ecologically friendly. Some examples of such policies include smart-growth and compact building design in the U.S. These policies and practices assume that dispersion of population and built-up structures have a direct link to ecological outcomes (Ewing, Pendall, and Chen 2002). The implicit suggestion is that concentrating humans in cities will yield ecological benefits for other species through fewer or a lack of disturbances of humans on other areas. However, in reality, whether other species are benefited by such policies is still an empirical issue. Recently, U.N. Environment Program Chief Klaus Toepfer (Reuters 2005) said the following:

> Cities pull in huge amounts of resources including water, food, timber, metals and people. They export large amounts of wastes including household and industrial wastes, wastewater and the gases linked with global warming. Thus, their impacts stretch beyond their physical borders, affecting countries, regions,

and the planet as a whole.

The widely available empirical link between species imperilment and human presence as measured by population density does not provide any basis for the assumed beneficial impact of the spatial configuration of humans on other species since the concepts of density and spatial configurations are quite different. Our understanding of the nature of the relationship between species imperilment and human presence can be enhanced considerably by analyzing the spatial configuration of human populations, controlling for density.

Other than human population density, alternative measures of human presence, for example human settlement pattern as measured by the spatial concentration of houses and Gini coefficient of population concentration, are barely identified and studied in the literature. Consequently, studies that link such measures of human presence and species imperilment are rare. Most of the available literature deals with human population density and its impacts on species (Forester and Machlis 1996; van Rensburg et al. 2004). The Miller and Hobbs study (2002) is a relevant example to illustrate this case. In an extensive review of the human settlement and land use change based on the papers published in *Conservation Biology* between 1995 and 1999, they found that fewer than 6% of the 217 papers considered human settlement in urban, suburban, or exurban areas in the study. This scenario suggests the paucity of information linking alternative measures of human presence such as human settlement or a Gini coefficient for population concentration to other species and associated outcomes.

Only a few recent studies have used alternative measures of human presence as compared to conventional population density alone. In a study of the effects of

household dynamics on resource consumption and biodiversity in 76 hotspot and 65 non-hotspot countries, Liu et al. (2003) found that there had been a rapid increase in the number of households and a reduction in the size of households, mostly in hotspot countries. These trends lead to higher per capita resource consumption and further pressure on biodiversity conservation. In a brown bear habitat study in northern Spain, Naves et al. (2003) considered the number of villages to represent human dispersion as additional variables to describe human activities, and they found that villages are negatively associated with bear presence. Brown and Laband (2006) studied the effect of human spatial distribution on species imperilment in the U.S., using a Gini coefficient measure for population concentration, but they failed to find a significant effect of human distribution on species imperilment. Thus, it is natural to expand this line of enquiry to gain more insights on the role of humans, particularly the human concentration, on species imperilment in different contexts, and this dissertation will take up this issue in a cross-country context for 5 species taxa.

2.2 Endemic Species, Biogeography, and Species Imperilment

Hotspots of biodiversity – areas particularly rich in species, rare species, threatened species, or some combination of these attributes – are being considered as focal areas to develop conservation priorities (Reid 1998). There are 25 hot spots identified around the world based on the two criteria: high concentration of endemic species and exceptional loss of habitat (Myers et al. 2000). Endemic species are the rare species with restricted distributional range delineated by soil, moisture, temperature, topography, and like abiotic and biotic factors. Generally, these species are fewer in population and are threatened with extinction. In a conflict mapping study between

biodiversity and human needs, Fox, Yonzon, and Podger (1996) found that endemic species are comparatively more vulnerable and threatened than other species.

In a recent study on the global test of biodiversity concordance and the importance of endemism, Lamoreux et al. (2006) found that global patterns of richness and endemism are highly correlated among amphibians, reptiles, birds and mammals. Even though they found a low correlation between global richness and endemism, aggregate regions selected for high levels of endemism captured significantly more species than expected by chance. Although areas high in endemism have long been targeted for the protection of narrow-ranging species, their findings provide evidence that endemism is also a useful surrogate for the conservation of all terrestrial vertebrates.

Kerr and Burkey (2002) studied endemism and diversity among 42 tropical moist-forest countries to understand the pattern of endemism across different taxa groups. The findings suggest that there is a similarity of endemism as expressed in percentage of species richness even after adjusting for country size and spatial effect for birds and mammals. It revealed that similar biological forces act to create tropical endemism among both birds and mammals, but the endemism and richness pattern for invertebrates and plants did not reflect the same pattern as that of birds and mammals.

Similarly, if we divide the countries into mainland and island that are characterized differently based on geography, microclimate, species composition, and human population distribution, a different pattern of species richness and endemism is expected. Species imperilment in island nations differs significantly from mainland nations (Czech and Krausman 1999). Islands are relatively poor in species richness but rich in species endemism because escape is virtually impossible. For example, one in six

plant species occurs on oceanic islands, and one in three of all known threatened plants is island-endemic (Fisher 2004). Frankel and Soule (1981) reported that the rate of extinction of island-specific species is much higher than mainland dwelling species. Presently, invasive species have been considered to be bigger threats than human activities in maintaining biodiversity in islands (Lasserre 2004). As discussed in the preceding paragraphs, it is clear that islands are unique in their biogeography. Therefore, a natural question is whether the uniqueness is common across all species taxa or is specific to some but not to all. This dissertation deals with this empirical question.

2.3 Economic Growth, Economic Freedom, Corruption, and Species Imperilment

Along with the debate about biodiversity loss, the nexus between economic growth or well-being and environmental degradation received wide-spread attention during the early 1990s following Simon Kuznets' (1955) famous study of economic growth and income inequality. This study suggested that there is an inverted U-shaped relationship between certain indicators of environmental degradation and economic growth, which later was referred to as the EKC hypothesis (Shafik and Bandyopadhyay 1992; Selden and Song 1994; Grossman and Krueger 1995). This hypothesis argues that negative environmental effects are at low levels during initial stages of economic development but will increase as the economic development proceeds towards higher stages. In addition, after a certain threshold of economic growth is reached, such effects starts diminishing, perhaps due to the introduction of environmentally-friendly industrial and agricultural technologies or change in preference or taste of an economic agent. For some specific indicators of environmental degradation, such as air and water pollution, this relationship is even described as N-shaped (Grossman and Krueger 1995; Torras and

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Boyce 1998). Common forms of environmental degradation studied in the past that support this hypothesis include certain types of air pollution (Selden and Song 1994; Grossman and Krueger 1995; Torras and Boyce 1998; Cole, Rayner, and Bates 2001), certain types of water pollution (Shafik 1994; Grossman and Krueger 1995; Torras and Boyce 1998), deforestation (Panayotou 1993), and threatened species (McPherson and Nieswiadomy 2005). However, recent contributors to EKC literature question its existence for specific forms of environmental degradation (Borghesi 1999; Meyer, van Kooten, and Wang 2003; Stern 2004) due to rapid technological and structural changes (de Bruyn, van den Bergh, and Opschoor 1998) and specialization and trade (Arrow et al. 1995; Stern, Common, and Barbier 1996).

Similarly, the nexus between corruption and economic freedom in a country with its economic well-being has also been widely acknowledged and documented in the literature. Corruption negatively affects investment activity and economic growth (Mauro 1995; Li, Xu, and Zou 2000; Mauro 2004), GDP per capita, international trade, and price stability (Dreher and Herzfeld 2005). Mo (2001) estimated that a one unit increase in corruption index reduces the economic growth rate by 0.545 percentage points and that the effect is passed on to the economy mostly through political instability. Li, Xu, and Zou (2000) found that corruption affects income distribution in an inverted U-shaped way and that it alone can explain a large proportion of Gini differential across developing and industrial countries. In a study of the determinants of unofficial activity in 69 countries, Friedman et al. (2000) found that corruption is associated with more unofficial activity, which in turn reduces tax revenue and thereby the official and total GDP of a country. In a study of African countries, Gyimah-Brempong (2002) found that

corruption decreases economic growth both directly and indirectly through decreased investment in physical capital.

The economic freedom and economic growth literature indicate a positive effect of economic freedom on growth but also acknowledge a strong publication bias (Doucouliagos 2005). In a survey of the benefits of economic freedom, Berggren (2003) presented mostly the positive effect of economic freedom on economic growth with some exceptions where economic freedom did not contribute in economic growth. Gwartney, Holcombe, and Lawson (2004) found that countries with institutions and policies consistent with economic freedom both grow more rapidly and achieve higher income levels. They further showed that institutional quality affects economic growth by affecting investment as well as productivity of resource use. In a study of economic freedom, per capita income and economic growth, Islam (1996) found that there is a positive relationship between economic freedom and per capita income in all countries. Similarly, Vega-Gordillo and Alverez-Acre (2003) and Cole (2003) found that economic freedom favors both the level and rate of economic growth.

Literature dealing with the direct link between corruption and economic well-being or economic freedom and economic well-being is abundant. Similarly, a direct link between economic well-being and species imperilment has also been suggested empirically in the context of EKC hypothesis. However, there is a paucity of literature that deals with the relationship between economic freedom and corruption and species imperilment. In retrospect, the indirect link between these factors and species imperilment can be drawn via their impact on economic well-being. Studies have just been started that link corruption and economic freedom to some sort of environmental

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degradation. Some of the emerging literature that touches on this link includes that of

Barret and Graddy (2000), Lopez and Mitra (2000), Lundstrom (2003), Carlsson and

Lundstrom (2003), Smith et al. (2003), Welsch (2004), and Pelligrini and Gerlagh (2005).

Lundstrom (2003) discussed the effect of specific economic freedom categories

on both the economic growth and the environment and highlighted some important

considerations for empirical work (see Lundstrom 2003 for details). Referring to

developing countries, Lopez and Mitra (2000) mentioned that corruption and lobbying by

vested interests are important sources of environmental degradation. In their study of the

effect of economic freedom on environmental quality, Carlsson and Lundstrom (2003)

found that economic freedom and increased freedom to trade reduce CO_2 emission.

However, they noted that if the government size is large, economic freedom increases

CO_2 emission. Welsch (2004) studied the role of corruption on growth and environment,

using water and air pollutions as indicators across the countries, and found that corruption

increases pollution in two ways: directly through reduced stringency of environmental

laws and enforcement and indirectly through reduced per capita income. While

presenting an empirical work on corruption, democracy and environmental policy,

Pellegrini and Gerlagh (2005) also claimed that corruption has a negative effect on

environmental policy stringency.

The study by Smith et al. (2003) on governance and loss of biodiversity is the

only one that directly links corruption with species at taxa level. They studied the

governance scores in corruption and combined species richness for birds and mammals

and found an inverse relationship between them, suggesting that increased corruption in a

country reduces the species richness for birds and mammals combined. They further

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studied the relationship between corruption and extent of national conservation priority areas represented by three indicators: endemic bird areas, biodiversity hotspots, and 25 focal terrestrial ecoregions, based on endemism, threat, and representativeness. The study found that all countries with conservation priority areas are more corrupt than countries without such areas.

Expanding this emerging literature on the impact of economic freedom index and corruption perceptions index on environmental outcomes would be relevant research for both the scientific community and policy makers. More importantly, empirical validation of the direct link between these indices and species imperilment at individual taxa level is a timely and informative work to all concerned and is believed to be the first of its kind.

2.4 Spatial Dependency, Weights Matrices, and Species Imperilment

The issues of spatial dependency, also called spatial autocorrelation, and spatial weights matrix are important considerations in studies that involve geographic data. As explained by Tobler's first law of geography (1970), "Everything is related to everything else, but near things are more related than distant things." There is an inherent dependency on spatial data. Biodiversity data almost always exhibit spatial autocorrelation (Kerr 2001). Spatial autocorrelation is the tendency for data points that are near to one another to be more similar than those that are widely separated. When spatial autocorrelation is present in the data, it violates the assumption of the independence of data values of the response variable in ordinary least squares regression analysis. The relevance of spatial autocorrelation on species imperilment is that the factors affecting species in one country may have spillover effects on neighboring countries' species. In such cases, spatial models represent the phenomena more

accurately than do ordinary models. Also, the spatial dependency might depend on the type of measure, generally referred to as spatial weights matrix, used to estimate the spatial dependency relationship. Anselin (1988) suggested two types of spatial regression models in empirical work: spatial lag and spatial error model. Spatial lag model is written as

$$y = \rho \mathbf{W} y + \mathbf{X} \beta + \varepsilon$$

where ρ is the coefficient of spatially lagged dependent variable, $\mathbf{W}$ is the spatial weights matrix, $\mathbf{X}$ is a N x K matrix of independent variables, β is a K x 1 vector of parameters, and ε is the normally distributed error term with a diagonal covariance matrix. The spatial error model is written as

$$y = \mathbf{X} \beta + \varepsilon$$

$$\varepsilon = y - \mathbf{X} \beta$$

$$\varepsilon = \lambda \mathbf{W} \varepsilon + \nu$$

where λ is the autoregressive coefficient, and ν is a homoskedastic and uncorrelated disturbance term.

The spatial weights matrix can be constructed by using multiple dependency measures to characterize the dependency relationship. For this research, four types of dependency measures are used to construct spatial weights matrices: 1st order adjacency, 2nd order adjacency, shared border length, and centroid distance between countries. First order adjacency refers to a simple binary adjacency (Moran 1948; Geary 1954) in which countries that share a common border are assigned a value of 1 in the spatial weights matrix, while countries that do not share a common border are assigned a value of 0. In the second order adjacency matrix, countries that directly share a common border and

countries with indirect adjacency (i.e., adjacency that is one country removed) are assigned a value of 1 in the spatial weights matrix. For the shared border adjacency matrix, the shared border length between any two countries is assigned in the spatial weights matrix. If countries do not share borders, then the value of 0 is assigned for those unrelated countries in the matrix. The centroid distance adjacency matrix consists of the distance between centroid points between any adjacent countries as a measure of spatial weights. Generally, spatial weights matrices are row standardized for computational purposes such that each row sums to one.

In a recent study of the regional disparities in the spatial correlation of state income growth in the U.S., Garrett, Wagner, and Wheelock (2005) used binary contiguity (simple adjacency) and inverse distance (the centroid distance) based weights matrices to capture the potential correlation among states. They performed spatial analysis, using spatial lag, spatial error, and both spatial lag and error in the same model based on both types of weight matrices. Bhattacharjee and Jensen-Butler (2005) argued that the choice of appropriate spatial weights is a central component of spatial models since it imposes a priori a structure of spatial dependence, which may or may not correspond to reality. They estimated a new spatial weight matrix based on a non-parametric approach and used a spatial error model in the spatial diffusion study of housing demands in the U.K. In their exploratory analysis of homicide rates in 78 U.S. counties, Messner et al. (1999) found evidence of positive spatial autocorrelation with a nonrandom distribution of homicides. However, they did not explore specific dependency structures. Moreover, Anselin (1988) identifies simple adjacency, higher-order adjacency, and centroid-based Euclidean distances as suggested adjacency measures in spatial econometric analysis.

There are a variety of tests to check spatial autocorrelation. Among those commonly used are the Moran's I (Moran 1948) and Geary's C (Geary 1954). Baltagi, Song, and Koh (2003) derived conditional and joint Lagrange Multiplier tests for spatial error correlation in a panel data setting using a Monte Carlo experiment. Anselin et al. (1996) developed a simple diagnostic test (adjusted Lagrange Multiplier test) for spatial dependence based on ordinary least squares residuals using 1st order spatial weights matrix. In this dissertation, queen contiguity based Moran's I test is used to check the spatial dependency on data employing all four spatial weights matrices. Moran's I is calculated as

$$I = \frac{(N/S_0)\Sigma_i\Sigma_j w_{ij}(x_i - \mu)(x_j - \mu)}{\Sigma_i(x_i - \mu)^2}$$

where w_{ij} is the element in the weights matrix corresponding to observation pair i and j, x_i and x_j are the observations for countries i and j with mean μ, and S_0 is a scaling constant equal to sum of weights ($S_0 = \Sigma_i\Sigma_j w_{ij}$). When the weight matrix is row standardized ($S_0 = N$), Moran's I is calculated as

$$I = \frac{\Sigma_i\Sigma_j w_{ij}(x_i - \mu)(x_j - \mu)}{\Sigma_i(x_i - \mu)^2}$$

The theoretical mean of Moran's I is -1/(N-1). A Moran's I coefficient larger than its expected value indicates positive spatial autocorrelation, and a coefficient less than its expected value indicates negative spatial autocorrelation. Standardized z-value is used to draw inferences. For Moran's I, the z-value is calculated as

$$Z_I = (I - E(I))/Sd(I)$$

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where $E(I)$ is the theoretical mean and $Sd(I)$ is the theoretical standard deviation. A positive and significant z-value for I indicates positive spatial autocorrelation (Anselin 2005).

The focus on spatial effects on cross-country studies of ecological/environmental phenomena is apparently lacking (Kerr and Currie 1995; Forester and Machlis 1996; Naidoo and Adamowicz 2001; McPherson and Nieswiadomy 2005). Even though Kerr and Burkey (2002) adjusted for spatial autocorrelation by adopting the conservative stance of assessing the number of degrees of freedom, McPherson and Nieswiadomy's study (2005) addressed the issue of spatial effects on species imperilment by rigorously using shared border length based spatial weights matrix. Still, issues related to adjacency measures other than shared border length and the spatial effects associated with independent variables need empirical support.

CHAPTER 3

SPATIAL CONCENTRATION OF HUMANS AND SPECIES IMPERILMENT

3.1 Introduction

It seems quite clear that the sheer number of humans (or any species) has a variety of ecological consequences (Kerr and Currie 1995; Thompson and Jones 1999; 2000). A successful species directly "crowds out" other species by appropriating habitat. As the population of a prey species increases, so does the population of any predator and/or symbiotic species, albeit with a temporal lag. In turn, a boom in the numbers of a predator species leads to a reduction in the numbers of the prey species, and population cycles among predator/prey species are well-documented.

However, while a link between the *spatial distribution* of humans (or human activity) and ecological outcomes has been conjectured, empirical support is lacking. For example, it has been suggested that intensively-managed timber, as a human activity, reduces the imperative to cut from "natural" forests, thus leaving greater area intact in undisturbed ecosystems (Sedjo and Botkin 1997; South 1999; Bowyer 2001). The implicit suggestion is that *in the aggregate,* there are ecological advantages (in terms of biodiversity enhancement, reduced soil disturbance, reduced ecosystem fragmentation, and the like) to more intensive human processing of a relatively smaller area of planted trees than less intensive human processing of a relatively larger area of naturally generated trees, for a given timber harvest level. Analogously, proponents of

the Smart-Growth principle of Compact Building Design advocate policies that encourage higher densities of humans in cities as a means of reducing the putative ecological harms caused by urban sprawl. As indicated on the Environmental Protection Agency (EPA) website: (http://cfpub1.epa.gov/sgpdb/glossary.cfm?type=topic),

> Compact building design refers to the act of constructing buildings vertically rather than horizontally, and configuring them on a block or neighborhood scale that makes efficient use of land and resources, and is consistent with neighborhood character and scale. *Compact building design reduces the footprint of new construction*, thus preserving green-space to absorb and filter rain water, reduce flooding and stormwater drainage needs, and lower the amount of pollution washing into our streams, rivers and lakes. (emphasis added).

A strong assumption forms the foundation for this Compact Building Design policy perspective: Not only does the sheer number of human beings matter, how the human population is distributed, generally speaking, matters also. In this regard, the analogy to intensively-managed forestry mentioned previously is virtually perfect, as indicated in this passage from the SmartGrowth.org website (www.smartgrowth.org/about/issues /issues.asp?iss=4),

> As we build, we replace our natural landscape - - forests, wetlands, grasslands with streets, parking lots, rooftops, and other impervious surfaces. The effect of this conversion is that stormwater, runoff which prior to development is filtered and captured by natural landscape, is trapped above impervious surfaces and runs off into streams, lakes, and estuaries, picking up pollutants along the

way. Runoff can be reduced through clustering of development, thereby leaving
larger open spaces and buffers. *Although compact development generates
higher runoff and pollutant loads within a development, total runoff and
pollutant loads are offset by reductions in surrounding undeveloped areas.*
(emphasis added)

The possibility that dispersion of the human population matters independently of
the level of human population can be illustrated by the example of two countries, A and
B, that are identical in every respect, including size of human population, land area,
percent of population living in urban areas, number and characteristics of ecological
niches, species diversity, and so on. In country A, the urban population is confined
completely within a single city of 100 square miles; in country B, the urban population is
distributed equally among 100 cities, each confined within a one square mile area. The
critical question is whether the ecological impact of the otherwise identical human urban
populations is the same across countries A and B.

There are good reasons to believe that the impacts would not be identical.
Depending critically on the precise location of both cities and ecologically imperiled
species, it seems likely that the impervious surface of the single urban area in A would
destroy a smaller number of species located in unique, geographically small, ecological
niches than the equivalent area of impervious surface distributed in smaller parcels in B,
which happen to coincide with a larger number of those unique, geographically small,
ecological niches. Yet, in fact, such location issues may be of empirically trivial
importance given that both countries require identical amounts of food, water, and other
resources to sustain their respective populations of humans. These life-sustaining

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resources are drawn from the entire country, not just the specific location in which the population is physically housed. Thus, the use of fertilizers and pesticides to boost agricultural harvests will be identical in the two countries, with identical impacts on their respective species' ecological imperilment.

There can be no doubt that, at an on-the-ground level of analysis, specific location decisions are critical to species imperilment. Concrete poured at specific location X may destroy the last remaining population of a rare flower but have a negligible ecological impact if poured at specific location Y. However, questions about the site-specific impact of humans on species imperilment are fundamentally different from questions about whether, *in the aggregate*, the number of ecologically imperiled species is influenced by the size-distribution of a fixed population of humans. Exactly where that existing population is physically located may indeed have ecological implications; however, these site-specific implications are quite separable, in theory, from the ecological implications of different size-distributions of the human population.

A significant intellectual foundation for the belief that the structural configuration of a fixed-size population has ecological implications was provided by Liu et al. (2003) and Keilman (2003). They argued that the intensity of resource use, and thus the aggregate environmental impact, is greater when a fixed population of human beings is distributed in smaller households than in larger households. There may be spatial implications of alternative household dynamics, but this need not necessarily be the case. Two or more households can occupy the same space as a single household, e.g., a residential house that has been divided into separate apartments. The result is that analysis of different household dynamics is not the same as analysis of different spatial

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distributions of a fixed-size population of humans.

Employing a cross-sectional analysis of the 49 continental states in the U.S., Brown and Laband (2006) investigated whether the structural organization of humans has an empirically significant *aggregate* impact, defined in terms of the ecological imperilment of plant and animal species. They constructed Gini coefficient measures of inequality in the concentration of human population in each state, using 4 indicators: (1) population, (2) the number of households, (3) night-time light distribution, and (4) distribution of roads. They failed to find evidence of a relationship between the distribution of human activity and the distribution of the number of ecologically imperiled species using NatureServe listings of species in each state that are at risk of extinction. In this chapter, the Brown and Laband line of empirical inquiry is extended by analyzing the relationship between the concentration of human populations and species imperilment for 5 taxa groups: breeding birds, mammals, reptiles, amphibians, and vascular plants, at aggregate and taxa level across 173 countries. Aggregate analysis is based on the combined information of all taxa.

3.2 Models, Data, and Methods

The number of ecologically imperiled species in a given country is modeled as depending on existing species richness (the number of different species), the level of endemism (the number of species found only within that area and nowhere else), and the level and spatial distribution of human activity. A general functional form is

Imperiled Species = f (Total # Species, # Endemic Species, Level of Human

$$\text{Activity, Concentration of Human Activity)} \qquad (3.1)$$

To avoid a dominant (explanatory) variable problem with total # species, #

imperiled species and # endemic species are converted to percentage form by dividing

each by the total # species, yielding

Percent Imperiled Species = f (Percent Endemics, Level of Human Activity,

$$\text{Concentration of Human Activity)} \qquad (3.2)$$

The percentage of imperiled species in a country is expected to increase as the

percentage of endemic species increases (McPherson and Nieswiadomy 2005; Brown and

Laband 2006). For a given rate of naturally-occurring extinctions at a specific point in

time, the number of ecologically imperiled species in a given geographic area will be

greater in areas characterized by relatively large numbers of species than in areas that do

not support much biodiversity. Further, by virtue of having wider ranges of moisture,

temperature, and geophysical attributes, some countries have greater numbers of unique

ecological niches than others, which support plant and animal species found nowhere

else. By definition, these endemic species are more likely than species with wider ranges

of habitat to be characterized by low populations.

The percentage of imperiled species is also expected to increase as the level of

human presence/activity increases (McKinney 2002b). Humans kill, harvest, or consume

other species directly to meet consumptive needs. Sheer population pressures held

constant, the type and extent of human activities clearly affect plant and animal

populations indirectly through alteration of habitat (Kerr and Currie 1995). The nature or

extent of these activities reflect man's economic well-being, and the exact relationship

between man's economic well-being and the impact on species imperilment is an

empirical matter.

The theoretical link between the economic well-being of humans and environmental degradation runs as follows: Desperately poor people are willing to accept increased environmental degradation as a necessary by-product of generating an improved material standard of living. As individuals' standards of living improve, they are able increasingly to turn their attention away from exploiting the natural environment for food, shelter, and other necessities of life and toward appreciation of the wonders of nature. That is, other species become valuable to humans not only because they can be used to improve man's well-being (in terms of providing food, shelter, medicines, etc.), but because their *existence* becomes important. In terms of empirical application, this implies an inverted U-shaped relationship between measures of economic well-being, such as per capita income, and measures of environmental degradation, the so-called Environmental Kuznets Curve (EKC).

Employing cross-sectional analysis and typically focusing on specific pollutants, a number of researchers have found empirical evidence that is consistent with the EKC (Cropper and Griffiths 1994; Selden and Song 1994; Grossman and Krueger 1995; Hilton and Levinson 1998; Rothman 1998; List and Gallet 1999; Hettige, Mani, and Wheeler 2000). However, these findings and the interpretations drawn from them have been criticized on the grounds that perhaps the reason that richer countries experience diminishing levels of environmental degradation is that they "export" their environmental harm to other, poorer countries (Arrow et al. 1995; Stern, Common, and Barbier 1996; de Bruyn, van den Bergh, and Opschoor 1998; Suri and Chapman 1998). A recent study looking at imperilment of birds and mammals across 115 countries in 2000 found evidence of an inverted U-shaped EKC (McPherson and Nieswiadomy 2005).

As the cited quotations in the introductory section make clear, advocates of the Smart-Growth principle of Compact Building Design argue that *in the aggregate,* the environment is harmed less by a concentrated human population than a dispersed human population. Thus, the predicted relationship between the percent of imperiled species and the concentration of human activity is negative, i.e., the percentage of threatened species decreases with increasing concentration of human presence or activity, and vice versa.

The regression model also includes a dummy variable for island nations as an additional explanatory variable. It is well-known that, in terms of species imperilment, island nations differ significantly from mainland nations (Czech, Krausman, and Devers 2000). Endemism is higher on islands, and because escape is virtually impossible, island-specific flora and fauna are particularly sensitive to the introduction of invasive species, such as the introduction of Australian *Brown Tree Snake* in Guam that preys on native lizards and birds.

Country-specific data on species by taxa (total species, endangered species, and endemic species) for each country in 2004 were taken from the World Resources Institute EarthTrends Environmental Portal (http://earthtrends.wri.org/searchable_db) (WRI 2004) that are published by the World Conservation Union (IUCN). The IUCN publishes a Red List that identifies species facing a relatively high risk of global extinction (i.e., those listed as Critically Endangered, Endangered or Vulnerable). Human population data was obtained from the United Nations Population Division (http://www.un.org/esa /population) (UNPD 2004). Data on per capita gross domestic product (GDP) at purchasing power parity were taken from the International Monetary Fund's World Economic Outlook database (http://www.imf.org/ external/pubs/ft/weo /2004/01/data

/index.htm) (IMF 2004). A Gini Coefficient measure of concentration in the human

population in each country is derived and used (Klein 2002), with index values ranging

from 0 (a uniformly dispersed population) to 1 (all population located in a cell). Using

ArcGIS, the world political map was superimposed on a LandScan 2002 gridded

population map (http://www.ornl.gov/gist/landscan/index.html) to create a population

distribution map for each country (ESRI 2002). The LandScan 2002 gridded population

distribution map is based on census count distributions to cells determined by proximity

to roads, land cover, slope, and night time lights and consisted of cells with

corresponding population values for each country (ORNL 2004). The Gini coefficient

index of population concentration (GCPOP) for a country was then computed from

unordered data as the *relative mean difference,* using the following formula as suggested

by Dixon et. al (1987) and Damgaared and Weiner (2000):

$$GCPOP = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n^2 \mu}$$

For this study, the above formula is simplified as:

$$GCPOP = \frac{(\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j| n_i n_j)}{2 \sum n_i^2 (\sum n_i x_i)/\sum n_i} = \frac{(\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j| n_i n_j)}{2 \sum n_i (\sum n_i x_i)}$$

where i = population counts (the number of cells that contain same number of people)

j = population values (the number of people per cell)

x_i = specific size population counts in a country

x_j = corresponding population values in a country

n_i = total number of population counts in a country

n_j = total number of population values in a country

μ = mean population size of a country

n = total number of countries

Equation 3.3 represents the reduced form model, which is estimated using the SAS Robust Regression weighted least squares technique. Two forms of the model were estimated, one for *aggregate* data and another for taxa-level data on mammals, birds, reptiles, amphibians, and vascular plants:

$$PIS_{ij} = \beta_0 + \beta_1 PES_{ij} + \beta_2 POPD_i + \beta_3 GCPOP_i + \beta_4 PCGDP_i + \beta_5 PCGDP^2 + \beta_6 ISLAND_i + \varepsilon_{ij},$$

(3.3)

where for each country (i = 1 to 173 depending on j, i.e. aggregate or specific taxa), PIS = % imperiled species, PES = % endemic species, POPD = population density (thousand person per sq. kilometer), GCPOP = Gini Coefficient Index for population concentration, PCGDP = per capita gross domestic product (GDP) at purchasing power parity (constant US $), ISLAND = a dummy variable (1 = island, 0 = mainland), and ε_{ij} = the error term.

The aggregate analysis is the combined analysis of all taxa and is based on the assumption that all species are affected by human activities and spatial distributions almost in the same manner. For example, if a natural area is cleared and inhabited by humans, it will threaten all plants, birds, mammals, reptiles, and amphibians living in that area.

3.3 Results and Discussion

The descriptive statistics for both aggregate and taxa level analyses are reported in Table 3.1. Both aggregate and taxa based statistics suggest that there are more endemic species in a country on average than imperiled species. Not all endemic species are imperiled species, except for mammals. At aggregate level, each country has 12.48% endemic species as compared to 1.9% threatened species. On average, about 3.5% of birds, 10.1% of mammals, 5.0% of reptiles, 12.2% of amphibians, and 1.3% of vascular

plants are under threat of extinction in each country. On the other hand, the same country harbors 3.85% of endemic birds, 4.5% of endemic mammals, 11.3% of endemic reptiles, 16.6% of endemic amphibians, and 13.3% of endemic vascular plants. Among the 5 taxa groups examined, amphibians are the most imperiled and endemic species.

Population density in the sample countries vary from 1.68 person/sq. Km. in Mongolia to 6,959 person/sq. Km. in Singapore, with an average of 177 persons/sq. Km./ country. Similarly, per capita GDP at purchasing power parity ranges from $591.9 in Sierra Leone to $39,535.2 in Norway. Actual GCPOP values range from 0.5898 to 0.9986. Singapore (0.5898), Togo (0.6515), and Rwanda (0.6529) have the most dispersed human populations; with large tracts of largely uninhabited land, Mongolia (0.9986), Australia (0.9981), and Canada (0.9975) have the most concentrated human populations. Out of 173 countries, 40 are islands with high population densities and high species richness. On average, each island country has 3.3% imperiled species, 25.7% endemic species, and 529 people per sq. km. while each mainland country has 1.48% imperiled species, 8.59% endemic species, and a population density of 74 persons per sq. km.

Table 3.1 Descriptive Statistics for Imperiled Species and Covariates

Variable		Aggregate	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
PIS	Mean	1.893	3.498	10.094	4.970	12.227	1.265
	SD	2.157	2.873	6.899	5.856	18.690	2.525
	Min.	0.423	0.000	0.000	0.000	0.000	0.000
	Max.	12.433	21.083	50.000	36.364	97.872	18.000
PES	Mean	12.478	3.793	4.523	11.303	16.566	13.270
	SD	17.351	7.834	9.274	16.958	24.271	18.379
	Min.	0.028	0.000	0.000	0.000	0.000	0.000
	Max.	87.070	45.476	61.818	90.741	91.667	89.999
POPD	Mean	177.664	159.91	159.91	159.91	156.09	174.95
	SD	671.667	552.50	552.50	552.50	564.01	651.71
	Min.	1.679	1.68	1.68	1.68	1.68	1.68
	Max.	6959.68	6959.68	6959.68	6959.68	6959.68	6959.68
GCPOP	Mean	0.869	0.872	0.872	0.872	0.874	0.868
	SD	0.096	0.102	0.102	0.102	0.095	0.095
	Min.	0.590	0.367	0.367	0.367	0.590	0.590
	Max.	0.999	0.999	0.999	0.999	0.999	0.999
PCGDP	Mean	9666.1	9712.6	9712.6	9712.6	9665.5	9531.1
	SD	9968.6	10343.0	10343.0	10343.0	10296.6	9974.9
	Min.	591.9	591.9	591.9	591.9	591.9	591.9
	Max.	39535.2	61596.8	61596.8	61596.8	61596.8	39535.2
ISLAND	Mean	0.227	0.231	0.231	0.231	0.196	0.274
	SD	0.421	0.423	0.423	0.423	0.398	0.448
	Min.	0.000	0.000	0.000	0.000	0.000	0.000
	Max.	1.000	1.000	1.000	1.000	1.000	1.000
N		110	173	173	173	163	117

With the exception of reptiles, the regression results (Table 3.2) indicate consistently that the percent of endemic species (PES) in a country is a strong, positive predictor of species' ecological imperilment, both at aggregate and at the taxa level of analysis. Endemic species are defined by unique ecological niches that they exploit. For the most part, these species are characterized by relatively small populations. Since ecological imperilment for a species is defined, in part, by a low population, a relatively large percentage of endemic species almost certainly will mean a relatively large percentage of ecologically threatened species. Likewise, the absolute level of human presence or activity in a country, defined in terms of population density, consistently is a significant, positive predictor of species' ecological imperilment even in the aggregate level, excepting reptiles and amphibians. Evidence of an Environmental Kuznets Curve relationship between a country's economic well-being, defined in terms of per capita GDP, and species imperilment has been depicted for birds and vascular plants but not for mammals, reptiles, and amphibians.

Of critical importance to the analysis is a statistically significant relationship between species' ecological imperilment and the Gini coefficient measure of human spatial concentration among birds, mammals, reptiles, and amphibians. However, the observed relationship (positive) and the predicted relationship (negative) are completely at odds in 3 of 4 cases. The implicit foundation for the Smart-Growth principle of Compact Building Design is that as a larger proportion of a fixed-size human population is concentrated in fewer locations, there is less ecological harm caused by the human population on the environment in the aggregate.

Table 3.2 Regression Results for Percent Imperiled Species

Variables	Aggregate	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.314**	-1.258	1.189	-3.035	16.325***	0.314
	(0.607)	(0.965)	(3.39)	(2.449)	(5.467)	(0.396)
PES	0.0234***	0.522***	0.312***	0.012	0.472***	0.01***
	(0.004)	(0.025)	(0.039)	(0.018)	(0.03)	(0.002)
POPD	0.161*	1.897***	8.145***	0.217	-1.42	0.325***
	(0.096)	(0.637)	(2.753)	(0.484)	(1.032)	(0.058)
GCPOP	-0.447	3.124***	6.926*	7.146**	-16.267**	0.113
	(0.731)	(1.132)	(3.998)	(2.901)	(6.433)	(0.476)
PCGDP	-0.007	0.113***	0.025	0.008	0.157	-0.033**
	(0.022)	(0.038)	(0.126)	(0.064)	(0.14)	(0.014)
$PCGDP^2$	0.0001	-0.003***	-0.002	-0.001	-0.005	0.001*
	(0.0006)	(0.001)	(0.004)	(0.002)	(0.003)	(0.0004)
ISLAND	0.269	-1.425***	1.312	2.25***	0.339	0.019
	(0.172)	(0.334)	(0.973)	(0.788)	(1.749)	(0.09)
N	110	173	173	173	163	117
R^2	0.4295	0.5974	0.3551	0.236	0.5149	0.2583

***, **, * denotes significance at 1%, 5%, and 10% levels respectively.

Figures in the parentheses are the standard errors.

This presumed relationship does indeed appear to characterize amphibians, but the observed relationship between species' ecological imperilment and concentration of human presence/activity is *positive*, not negative, among birds, mammals, and reptiles. This means that concentrating the human population in cities is associated with more, not fewer, ecologically imperiled species across these three taxa, a finding completely at odds

with the expressed claims on various Smart-Growth websites. The result reveals that there is no statistically significant relationship between geographic concentration of the human populations and ecological imperilment among vascular plants and aggregated data.

Finally, results are mixed with respect to the ecological imperilment of species found on islands. As expected, it is found that the island-based reptile species are more imperiled than continent-based reptiles. However, island-based bird species are less imperiled than continent-based bird species, and also there is no evidence of a statistically significant impact of this latter finding, which contradicts the record on extinctions— higher for island-based birds than continent-based birds. Of course, this differential record of extinction may imply that the island-based bird species are still living (thus included in our sample) and likely are not imperiled.

3.4 Concluding Remarks

While it is possible that deliberate clustering of humans in high-density urban areas is preferable, from an ecological standpoint, to a more dispersed human population, the only available anecdotal evidence suggests just the opposite: The last century of dramatically increased urbanization almost everywhere in the world is associated with significant global environmental degradation. However, this also has occurred during a period of rapid population growth, so separating association from causation is problematic. People who live in cities need to be fed, which implies a significant agricultural effort that likely distresses natural systems. The materials that are used to build and maintain the cities require significant extractive industries and power generation. These activities also are associated with environmental degradation. Thus, it

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is not at all clear whether accidental or deliberate configuration of the human population into densely populated urban areas actually will provide significant environmental benefits.

This empirical finding casts doubt on the presumption that environmental impacts are minimized when human presence or activity is spatially concentrated. While it may be that localized observations on specific pollutant loadings seem consistent with this presumption, at a more encompassing scale and measure, reflected in species imperilment, mixed evidence is found. Although concentration in the human population may, on a broad scale, reduce ecological stresses on amphibians, they appear to have no effect on vascular plants and may actually increase ecological stresses on birds, mammals, and reptiles.

In the preceding analysis, the concern raised by Tobler's first law of geography (Tobler 1970) about the spatial dependency in the data has not been addressed, which might be a potential reason for our mixed results. The next chapter explores the relevance of Tobler's law and associated spatial dependency issues in the context of species imperilment for five taxa groups.

CHAPTER 4

SPATIAL AUTOCORRELATION AND SPECIES IMPERILMENT

4.1 Introduction

Modeling the determinants of species imperilment using country-specific data

may be complicated by the fact that factors influencing species imperilment extend or

operate beyond arbitrary political boundaries. In other words, factors that influence

species imperilment in one country also may influence species imperilment in

neighboring countries. This means that empirical analyses of natural phenomena that

must be conducted using country-level data frequently are characterized by spatial

autocorrelation. Put differently, the possibility of spatial autocorrelation reflects a

concern that if species face relatively high risks in one country, the same species in

neighboring countries may be affected similarly by spillover threats.

Although arguably a large number of both naturally-occurring and anthropogenic

phenomena are characterized by spatial autocorrelation, there has been relatively little

empirical analysis of the structure of spatial adjacency configurations. There are a

number of ways to specify the structure of the spatial dependency of one country on other

countries. Legendre (1993) suggests using several possible metrics to analyze ecological

data: (1) a linear combination of the geographic coordinates of sampling stations, (2) a

first-order Euclidean distance matrix, (3) inverse Euclidean distance, and (4) inverse of

the square of Euclidean distance. In their pathbreaking work, McPherson and

Nieswiadomy (2005) analyzed factors that influenced the percent of threatened birds and mammals across 115 countries in 2000. Using a length (percent) of common border formulation of the spatial relationship between countries, their tests revealed the presence of positive spatial dependency. McPherson and Nieswiadomy then report estimation results for models that included spatial lag terms, which were found to be highly significant for mammals and marginally significant for birds.

In addition to the percent of shared border structure of the dependency relationship between countries, several other structures have been proposed (Anselin 1988): (1) a binary contiguity matrix (Moran 1948; Geary 1954) in which countries that share a common border are assigned a value of 1 while countries that do not share a common border are assigned a value of 0; (2) a second or higher-order adjacency matrix, in which countries that directly share a common border and countries with indirect adjacency (i.e., adjacency that is one or more countries removed) are assigned a value of 1; and (3) the distance between centroid points located in two adjacent countries.[1] With this guidance, the spatial relationship between two countries is constructed in terms of

   (a) simple adjacency,

   (b) higher-order (simple plus one-country removed) adjacency,

   (c) distance between adjoining countries' centroid locations, and

   (d) percentage of shared border.

Both spatial lag models and spatial error models have been employed to capture geographic spillover effects (see especially Anselin, 1988). Estimation of spatial error

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[1] Distance between centroid points also is used in gravity models that seek to explain the movement of goods between two locations (Bergkvist 2000; Polyakov and Teeter 2005).

and spatial lag models permit one to test for, and control for, the presence of spatial autocorrelation. In the absence of such a control, a model may be plagued by a significant omitted variable problem, leading to biased coefficient estimates. Therefore, spatial error and spatial lag models serve a useful function in terms of improving statistical efficiency. However, these general corrections for spatial autocorrelation do not shed any light on the non-spatial *nature* of the dependency.

To illustrate this, the work of McPherson and Nieswiadomy (2005) should be considered. Explanatory variables in their models include the percentage of species endemic to a country, human population density, and per capita GDP. Among birds and mammals, they found statistically significant evidence of spatial autocorrelation and the evidence of an Environmental Kuznets Curve relationship: Species imperilment rises with per capita income, at a diminishing rate (McPherson and Nieswiadomy 2005).[2] The spatial autocorrelation term indicates only that species imperilment in country A is influenced significantly by adjacent countries; it reveals nothing about specific aspects of

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[2] Employing cross-sectional analysis and typically focusing on specific pollutants, a number of researchers have found empirical evidence that is consistent with the EKC (Cropper and Griffiths 1994; Selden and Song 1994; Shafik 1994; Grossman and Krueger 1995; Hilton and Levinson 1998; List and Gallet 1999; Hettige, Mani, and Wheeler 2000). However, these findings and the interpretations drawn from them have been criticized on the grounds that perhaps the reason that richer countries experience diminishing levels of environmental degradation is that they 'export' their environmental harm to other, poorer countries (Arrow et al. 1995; Stern, Common, and Barbier 1996; de Bruyn, van den Bergh, and Opschoor 1998; Rothman 1998; Suri and Chapman 1998). That is, instead of manufacturing environmentally unfriendly items in their own countries and subjecting themselves to environmental degradation, people living in rich countries merely purchase those goods from manufacturers living in other countries, who then are the ones subject to the environmental problems associated with production. International trade permits global NIMBY (not in my backyard), in which the poorest countries voluntarily become the environmental dumping grounds for the richest countries.

those adjacent countries that affect species imperilment in country A. More to the point, it is possible that per capita GDP in adjacent countries affects species imperilment in country A but that the specification of the spatial autocorrelation control in purely spatial terms aggregates all possible contributory effects, thereby inhibiting the researchers from ascertaining whether per capita GDP in adjacent countries affects species imperilment in country A. Likewise, human population density exerts a positive and statistically significant impact on species imperilment of mammals. It seems reasonable to speculate that population density in surrounding countries also might influence species imperilment among mammals in country A. Indeed, it is possible that the spatial dependency between two countries is driven largely, perhaps completely, by per capita GDP or human population density, but this possibility is not subject to examination when using the general form of the spatial dependency correction.

All models of species imperilment that include controls for spatial autocorrelation have defined the between-country dependency purely in spatial terms (what is referred to as general dependency). However, there is nothing that prevents from defining the spatial relationship between two countries in terms of specific variables, such as per capita income, population density, etc. As noted previously, the general form of the simple adjacency weights matrix assigns a value of 1 to countries that share a border with country A and a 0 to countries that do not share a border with country A. However, one could assign a value equal to the per capita GDP or population density of countries that border on country A to create a specific form of the simple adjacency weights matrix.

This chapter extends this general line of inquiry on spatial issues by (1) confirming the advisability of controlling for spatial autocorrelation in models focusing

on imperilment of birds, mammals, reptiles, amphibians, and vascular plants; (2) comparing the performance of different definitions of the spatial dependency between countries; and (3) exploring the consequences of including both general and specific controls for spatial autocorrelation in country-level models of species imperilment.

4.2 Models, Data, and Methods

A number of factors, both natural and anthropogenic that influence species ecological imperilment have been confirmed empirically by previous researchers (Naidoo and Adamowicz 2001; McPherson and Nieswiadomy 2005; Pandit and Laband 2005): (1) *species endemism*: By virtue of having wider ranges of moisture, temperature, and geophysical attributes, some countries have greater numbers of unique ecological niches than others, which support plant and animal species found nowhere else. By definition, these endemic species are more likely than species with wider ranges of habitat to be characterized by low populations. Therefore, countries that are characterized by greater numbers (percentages) of endemic species should also be characterized by greater numbers (percentages) of ecologically imperiled species.

(2) *human population density*: Humans kill/harvest, or consume other species directly to meet their needs and indirectly by appropriating space and habitat. Consequently, greater human population density should be reflected in higher levels of species imperilment.

(3) *human activity*: Sheer population pressures held constant, the type and extent of human activities clearly affect plant and animal populations indirectly through alteration of habitat. The nature or extent of these activities reflect man's economic well-being, and the exact relationship between man's economic well-being and the impact on species imperilment is an empirical matter. Per capita GDP at purchasing power parity is

included in the analysis to be an indicator of economic well-being.

(4) s*patial concentration in the human population*: One of the principles of the "Smart-Growth" movement in the U.S. is "Compact Building Design," which encourages high-density human living arrangements in the belief that, in the aggregate, there are beneficial ecological consequences. That is, for a fixed-size human population, life on earth is stressed less by spatially configuring that human population in a small number of densely-packed cities than by a more dispersed pattern. In previous empirical analysis that did not control for spatial autocorrelation (Pandit and Laband 2005), they used a Gini-coefficient measure of concentration to test whether spatial concentration in human populations is associated with ecological benefits in the aggregate form of reduced incidence of species' ecological imperilment. While the evidence suggests that the spatial concentration of humans is statistically related to species imperilment for certain taxa, in a majority of cases, the impact observed was *positive*, not negative as presumed by advocates of compact building design. That is, the spatial concentration of the human population typically was associated with higher rates of species ecological imperilment, not lower rates.

(5) i*sland nations*: Endemism is higher on islands, and because escape (for all taxa except birds) is virtually impossible, island-specific flora and fauna are particularly sensitive to the introduction of invasive species, e.g., *Homo sapiens* and the species that they bring with them, such as cats, snakes, etc..

Based on these documented influences on species imperilment, the following reduced form model for taxa-level data on mammals, birds, reptiles, amphibians, and vascular plants is estimated

$$PIS_{ij} = \beta_0 + \beta_1 \overset{(+)}{PES_{ij}} + \beta_2 \overset{(+)}{POPD_i} + \beta_3 \overset{(-)}{GCPOP_i} + \beta_4 \overset{(+)}{PCGDP_i} + \beta_5 \overset{(-)}{PCGDP^2} +$$

$$\beta_6 \overset{(+)}{ISLAND_i} + \varepsilon_{ij},$$

(4.1)

Augmenting the Eq. (4.1) by nature of spatial dependency (k) and the adjacency measures

(l), the spatial specification of the model is

$$PIS_{ij} = \beta_0 + \beta_1 PES_{ij} + \beta_2 POPD_i + \beta_3 GCPOP_i + \beta_4 PCGDP_i + \beta_5 PCGDP^2 +$$

$$\beta_6 ISLAND_i + SA_{ijkl} + \varepsilon_{ijkl},$$

(4.2)

where for each country, PIS = the percentage of species that were on the World

Conservation Union's (IUCN) Red List of threatened species in 2004, PES = the percent

of endemic species, POPD = population density (thousand persons per square kilometer),

GCPOP = a Gini Coefficient Index for concentration in the human population, PCGDP =

per capita gross domestic product (GDP) at purchasing power parity (in constant US $ - -

pegged to year 2000), ISLAND = a dummy variable (1 = island, 0 = mainland), i =

sample countries: 1 to N depending on taxa j (5 taxa groups), k = is the lag or the error

nature of spatial dependency, l = is the one of the four adjacency measures : simple

adjacency or 2nd / higher-order adjacency or centroid distance or percentage of shared

border length, SA_{ijkl} = the spatial autocorrelation term for country i, taxa j, spatial model

k, and adjacency measure l, and ε_{ijkl} = the error term. The expected signs are in

parentheses above each variable in Eq. (4.1).

Using the same data described in the previous chapter, Eq. (4.2) is estimated both

with and without controls for spatial autocorrelation, using the SAS Robust Regression

weighted least squares technique. First, tests for spatial autocorrelation for all spatial

dependency measures are presented. Second, the regression results based on all 4 spatial

dependency measures to identify the best spatial model are presented. Finally, the general and specific lag based results are presented for all taxa groups, focusing on parsimonious spatial adjacency measure identified during the analysis.

4.3 Results and Discussion

4.3.1 Spatial Autocorrelation and Dependency Structures

Moran scatter plots to depict the spatial autocorrelation for percent imperiled species by taxa are presented in Figure 4.1, where the x-axis represents the percent imperiled species and the y-axis represents the spatial lag for percent imperiled species based on simple adjacency measure. In the scatter plots, the quadrants correspond to different types of spatial autocorrelation: high-high and low-low for positive spatial autocorrelation, and low-high and high-low for negative spatial autocorrelation. Figure 4.2 presents the nature of these different spatial autocorrelations for imperiled birds in the form of a cluster map. Figure 4.3 indicates the severity of spatial autocorrelation for imperiled birds that is evidenced by a significance map. The map of sample countries (see the list of sample countries in appendix V) and the cluster and significance maps for remaining taxa are given in Appendices I and II.

Sample statistics are reported in Table 4.1. Ordinary and robust Lagrange Multiplier (LM) test statistics based on Moran's I test for all taxa groups and 3 of the 4 dependency structures are presented in Table 4.2. Additionally, the Likelihood Ratio (LR) test statistics are presented in Table 4.2 to evaluate the structure of spatial dependency for particular taxa.

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Figure 4.1 Moran Scatter Plots for Imperiled Species by Taxa based on Simple

Adjacency
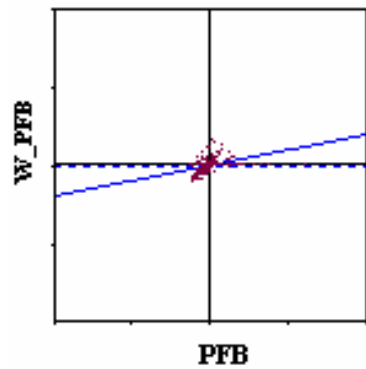
Moran's I for Birds = 0.1696
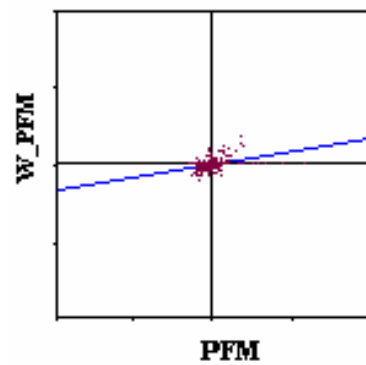
Moran's I for Mammals = 0.1273
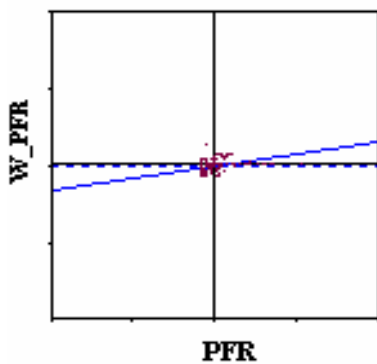
Moran's I for Reptiles = 0.1504
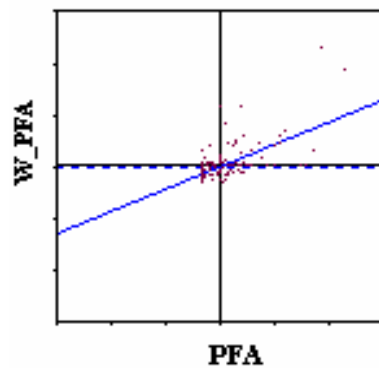
Moran's I for Amphibians = 0.4373
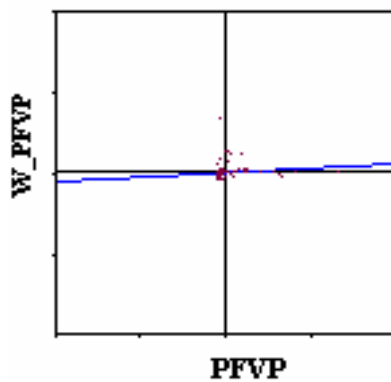
Moran's I for Vascular Plants = 0.1969

Figure 4.2 Cluster Map for the Nature of Spatial Autocorrelation Among Birds
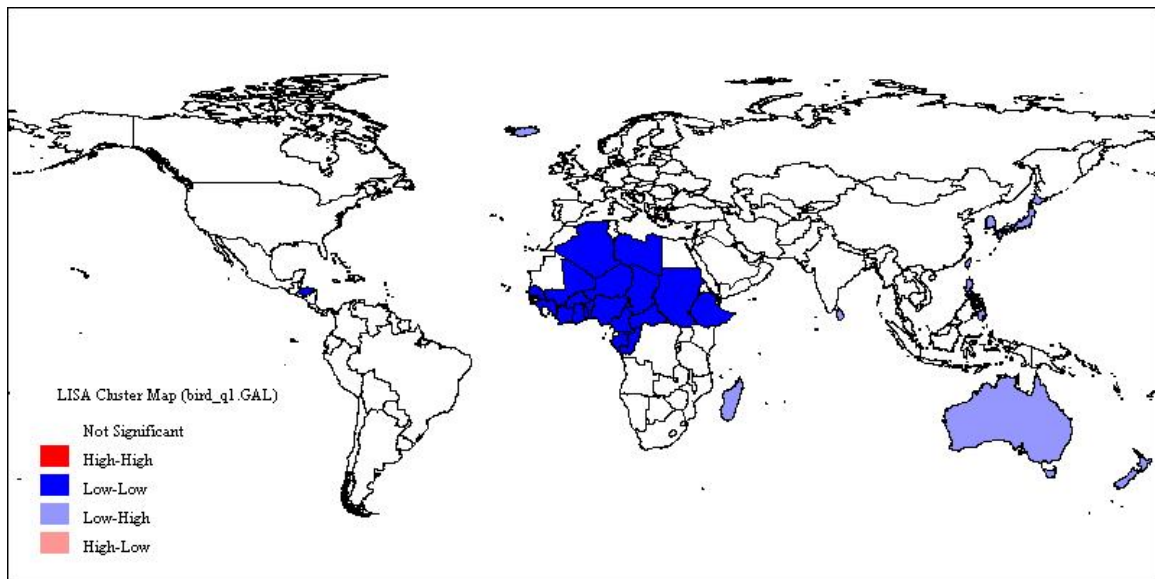
Figure 4.3 Significance Map for the Intensity of Spatial Autocorrelation Among Birds
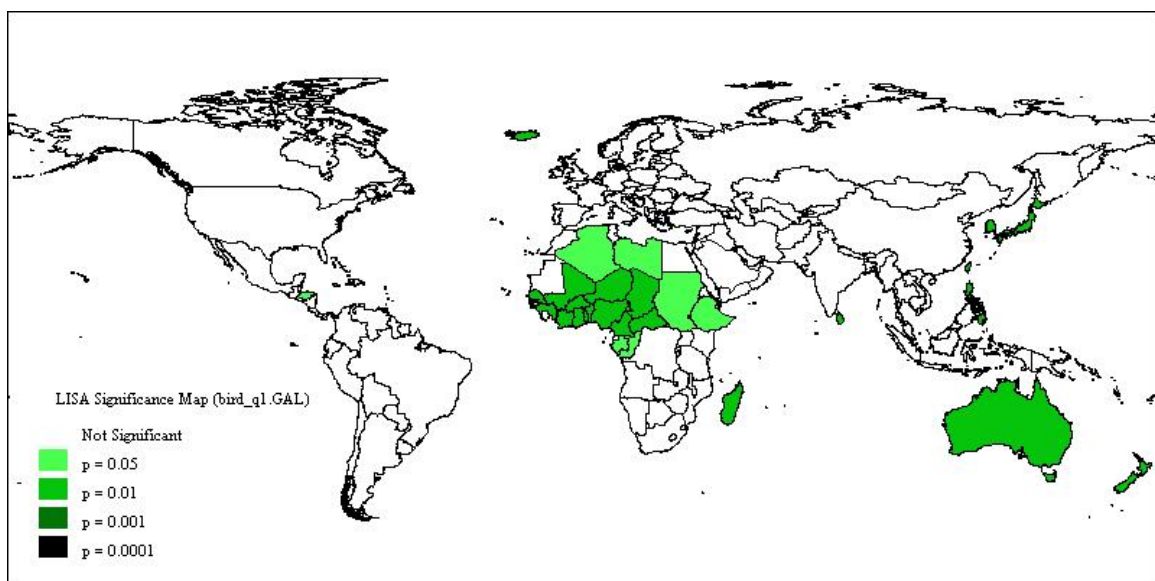
The Moran's I test only reveals the presence or absence of spatial autocorrelation generally; it does not identify the source of the spatial dependency. Spatial error and spatial lag models must be estimated separately to determine the impact of spatial correlation. The test results confirm the McPherson and Nieswiadomy (2005) finding of statistically significant spatial dependency in models of bird and mammal imperilment. Going further, the results suggest additional evidence of significant spatial dependency in models of species imperilment among reptiles and amphibians but less evidence of significant spatial dependency in models of species imperilment among vascular plants. The only circumstance that suggests a statistically significant spatial dependency in models involving vascular plants is observed when the dependency is structured as simple adjacency. Vascular plants aside, both measures of adjacency-based dependency are consistently significant across the other 4 taxa groups. Centroid distance-based dependency is significant among the birds and reptiles.

Once spatial autocorrelation has been confirmed, there is no specific test to determine which adjustment (spatial lag versus spatial error) is appropriate. Although McPherson and Nieswiadomy (2005) favor a spatial lag model over a spatial error model, Anselin (2005) suggests basing such preference on a sequential judging of ordinary and robust Lagrange Multiplier statistics. If ordinary LM test statistics are significant for both spatial lag and error dependency, the spatial model selection should be based on the significance of robust LM test statistics. When both ordinary LM test statistics are significant but none of the robust LM test statistics are, the structure of the spatial dependency should be decided based on the most significant ordinary LM test statistic. In almost all cases that are investigated, the LM test statistics yielded higher values

for spatial error-based dependency than for spatial lag-based dependency.

Table 4.1 Descriptive Statistics for Imperiled Species and Covariates by Taxa

Variable		Birds	Mammals	Reptiles	Amphibians	Vascular Plants
PIS	Mean	3.498	10.094	4.970	12.227	1.265
	SD	2.873	6.899	5.856	18.690	2.525
	Min.	0.000	0.000	0.000	0.000	0.000
	Max.	21.083	50.000	36.364	97.872	18.000
PES	Mean	3.793	4.523	11.303	16.566	13.270
	SD	7.834	9.274	16.958	24.271	18.379
	Min.	0.000	0.000	0.000	0.000	0.000
	Max.	45.476	61.818	90.741	91.667	89.999
POPD	Mean	159.91	159.91	159.91	156.09	174.95
	SD	552.50	552.50	552.50	564.01	651.71
	Min.	1.68	1.68	1.68	1.68	1.68
	Max.	6959.68	6959.68	6959.68	6959.68	6959.68
GCPOP	Mean	0.872	0.872	0.872	0.874	0.868
	SD	0.102	0.102	0.102	0.095	0.095
	Min.	0.367	0.367	0.367	0.590	0.590
	Max.	0.999	0.999	0.999	0.999	0.999
PCGDP	Mean	9712.6	9712.6	9712.6	9665.5	9531.1
	SD	10343.0	10343.0	10343.0	10296.6	9974.9
	Min.	591.9	591.9	591.9	591.9	591.9
	Max.	61596.8	61596.8	61596.8	61596.8	39535.2
ISLAND	Mean	0.231	0.231	0.231	0.196	0.274
	SD	0.423	0.423	0.423	0.398	0.448
	Min.	0.000	0.000	0.000	0.000	0.000
	Max.	1.000	1.000	1.000	1.000	1.000
N		173	173	173	163	117

Table 4.2 Spatial Autocorrelation Tests[3]

Moran's I Spatial Autocorrelation Tests (percent imperiled species by taxa, normal approximation)

Taxa	Spatial Weight Measure	Moran's I	Mean	Std. Dev.	P-value	LM Test (Z-value)		LR Test (Z-value)	
						Lag	Error	Lag	Error
Birds	Simple Adjacency	0.1696	-0.0048	0.0535	0.002	13.743***	22.543***a	17.661***	46.143***
	Higher Adjacency	0.1485	-0.0046	0.0325	0.002	14.568***	25.648***a	13.993***	32.466***
	Distance center-to-center	0.2988	-0.0054	0.0217	0.001	10.428***	28.471***a	7.517***	12.209***
Mammals	Simple Adjacency	0.1273	-0.0053	0.0527	0.014	4.849**	6.139**	9.424***	21.442***
	Higher Adjacency	0.1080	-0.0049	0.0335	0.005	6.210**	10.132***b	8.92***	18.850***
	Distance center-to-center	0.0965	-0.0048	0.0213	0.002	0.919	1.461	0.44	0.56
Reptiles	Simple Adjacency	0.1504	-0.0042	0.0563	0.006	2.764*a	10.422***a	9.209***	32.548***
	Higher Adjacency	0.1270	-0.0071	0.0328	0.004	1.862	12.384***a	4.757**	27.865***
	Distance center-to-center	0.1264	-0.0058	0.0214	0.002	7.818***c	4.245**	5.416**	3.875**

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Table 4.2 Spatial Autocorrelation Tests[3] (Cont'd)

Moran's I Spatial Autocorrelation Tests (percent imperiled species by taxa, normal approximation)

Taxa	Spatial Weight Measure	Moran's I	Mean	Std. Dev.	P-value	LM Test (Z-value) Lag	LM Test (Z-value) Error	LR Test (Z-value) Lag	LR Test (Z-value) Error
Amphibians	Simple Adjacency	0.4374	-0.0069	0.0556	0.001	50.954***a	46.679***c	61.932***	71.184***
	Higher Adjacency	0.3683	-0.0066	0.0348	0.001	67.041***a	59.779***c	45.113***	59.609***
	Distance center-to-center	0.2364	-0.005	0.0245	0.001	6.449**b	2.151	5.757**	1.810
Plants	Simple Adjacency	0.1969	-0.0094	0.049	0.006	2.910*	3.540*	0.137	2.003
	Higher Adjacency	0.1258	-0.0061	0.0379	0.007	0.015	0.070	0.028	0.134
	Distance center-to-center	0.0555	-0.0075	0.0285	0.025	0.245	0.456	0.341	0.729

Asterisks represents the significance of Lagrange Multiplier (LM) and Likelihood Ratio (LR) lag and error tests at different significance levels (*' for 10%, '**' for 5% and '***' for 1% significance).

All the model tests are performed in GEODA. Tests based on neighboring boarder length is not supported by GEODA, so the spatial lag and error matrices are computed manually and used in the robust regressions as separate variables.

a, **b**, and **c** represent the significance of Robust LM test respectively at 1%, 5%, and 10% significance levels when both LM lag and error tests are significant for particular spatial measure. In such cases, the significance of the Robust LM test determines the dependency structure of the model (Anselin, 2005).

[3] The current version of GEODA, the software used to conduct the spatial analysis, was not able to handle shared border length in computing the spatial weights matrix that is required for the spatial autocorrelation tests. For the shared-border dependency term that was included in the regression models, the spatial error and spatial lag matrices are manually formulated.

The Jarque-Bera test for normality and Breush-Pagan test for heteroscedasticity in OLS models revealed the residuals' non-normality and non-constant variance for all taxa groups. Furthermore, the Koenker-Bassett test, which is based on normalized residuals, reaffirmed the non-constant error variance (Table 4.3). In such cases Pindyck and Rubinfield (1990) recommend using weighted least squares to correct the heteroscedastic nature of the data. Thus, Eq. (4.2) is estimated using the Robust Regression weighted least squares technique in SAS due to its ability to detect outliers in both the dependent variable (influential data points) and independent variables (leverage data points) in the analysis. Robust Regression is a new SAS analytical tool that provides an alternative to an Ordinary Least Squares (OLS) Regression model when the fundamental assumptions of OLS about the data (homoscedasticity, independent observations, and residuals' normality) are violated. It provides resistant (stable) results in the presence of outliers by assigning different weights to the outlying observations (Chen 2002).

Table 4.3 Tests for Residual Normality (♣) and Heteroscedasticity (♦) Under Ordinary Least Squares Assumptions

Taxa	Jarque-Bera Test♣	Breusch-Pagan Test®♦	Koenker-Bassett Test®♦
Birds	291.49***	314.977***	75.362***
Mammals	977.302***	131.421***	20.457***
Reptiles	168.00***	104.98***	34.787***
Amphibians	413.917***	75.952***	16.825***
Plants	1008.278***	151.889***	20.299***

*** represents statistical significance at the 1percent level

® The Breusch-Pagan test is based on ordinary residuals whereas the Koenker-Bassett test is based on studentized (normalized) residuals.

Table 4.4 shows results of three alternative estimations for each taxa group: (a) a model that contains no adjustment for spatial autocorrelation, (b) a spatial lag model, and (c) a spatial error model. In these estimations, the spatial dependency between countries is structured as simple adjacency for reasons that are discussed presently.[4]

Table 4.4 shows the importance of the presence of spatial dependency, which reports the percentage increase in explanatory power (R^2 value) from the models containing no spatial adjustment to the spatial lag and spatial error models. Among the birds, mammals, amphibians and vascular plants, the percentage increase in model explanatory power is greater for models containing a spatial error structure (Lag ERROR) of dependency than a spatial lag structure (Lag PIS). Among the reptiles, the percentage increase in model explanatory power was greater for models containing the spatial lag structure.

As expected, the percentage of imperiled species in a country is positively, and strongly, influenced by the percentage of endemic species. Excepting for reptiles, this finding is consistent across all taxa groups in all model specifications. However, aside from the spatial lag or error term (in model 2 and 3), the percentage of endemic species is the only variable that consistently exerts a significant influence on the percentage of imperiled species, with the exception of reptiles, and that coefficient is positive with a χ^2-value greater than 1.

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[4] Each spatial error and spatial lag model are also estimated, using alternative structures of the spatial relationship between countries with the reported findings being fully representative (see Appendix –III).

Table 4.4 Simple Adjacency Based Weighted Least Squares Regression Results for Factors Influencing Species Imperilment

Model 1: Ordinary Models with No Spatial Lag/Error

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-1.2583	1.1892	-2.8747	16.3253***	0.3143
	(0.9645)	(3.3901)	(2.456)	(5.467)	(0.3961)
PES	0.5221***	0.3115***	0.0114	0.4719***	0.0103***
	(0.0251)	(0.0388)	(0.0184)	(0.0297)	(0.0024)
POPD	1.8970***	8.1445***	0.1754	-1.4203	0.3245***
	(0.6371)	(2.7534)	(0.4865)	(1.0321)	(0.0579)
GCPOP	3.1242***	6.9264*	6.7099**	-16.2673**	0.1125
	(1.1324)	(3.9984)	(2.9383)	(6.433)	(0.4764)
PCGDP	0.1130***	0.0250	0.0750	0.1573	-0.0328**
	(0.038)	(0.126)	(0.0957)	(0.1401)	(0.0138)
$PCGDP^2$	-0.0030***	-0.0024	-0.0035	-0.0051	0.0007*
	(0.0011)	(0.0038)	(0.0028)	(0.0033)	(0.0004
ISLAND	-1.4254***	1.3122	2.2621***	0.3394	0.0193
	(0.3342)	(0.9734)	(0.7888)	(1.7488)	(0.0902)
N	173	173	173	163	117
R^2	0.5974	0.3551	0.2447	0.5149	0.2565

Model 2: Spatial Lag Models

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.4433*	8.5747***	2.6200	21.5132***	0.3965
	(0.7691)	(2.7513)	(2.0680)	(5.6796)	((0.3900)
PES	0.2948***	0.2666***	0.0085	0.4228***	0.0100***
	(0.0145)	(0.0314)	(0.0148)	(0.0306)	(0.0023)
POPD	-0.0492	3.3128*	-0.2478	-1.7865	0.3192***
	(0.1490)	(1.9578)	(0.3929)	(1.0984)	(0.0568)
GCPOP	1.1404	-1.1125	1.7155	-20.2142***	0.0368
	(0.8931)	(3.2367)	(2.4110)	(6.6796)	(0.4681)
PCGDP	0.0439**	0.1769*	0.0480	0.2777*	-0.0315**
	(0.0196)	(0.1006)	(0.0524)	(0.1482)	(0.0135)
PCGDP^2	-0.0010**	-0.0058*	-0.0014	-0.0069**	0.0007*
	(0.0005)	(0.0030)	(0.0012)	(0.0035)	(0.0004)
ISLAND	-0.6356***	1.0995	0.9469	-1.8874	-0.0129
	(0.2454)	(0.8487)	(0.6529)	(1.8142)	(0.0896)
Lag PIS	1.6078***	4.5759***	4.6394***	7.2509***	0.1692**
	(0.1653)	(0.6190)	(0.5557)	(1.2010)	(0.0784)
N	173	173	173	163	117
R^2	0.7601	0.5607	0.5203	0.5514	0.3164
% Δ in R^2 From Model 1	+27.2	+57.9	+112.6	+7.1	+23.4

Model 3: Spatial Error Models

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.7395	5.1574**	0.0769	15.6050***	0.2988
	(0.6161)	(2.5390)	(2.1422)	(4.9522)	(0.3897)
PES	0.4242***	0.3136***	0.0040	0.5075***	0.0104***
	(0.0213)	(0.0343)	(0.0158)	(0.0273)	(0.0023)
POPD	0.0684	-0.8809*	-0.1917	-1.3169	0.3321***
	(0.1280)	(0.4956)	(0.4197)	(0.9351)	(0.0571)
GCPOP	1.1123	3.1009	3.5045	-13.8980**	0.1674
	(0.7351)	(2.9988)	(2.5364)	(5.8160)	(0.4693)
PCGDP	0.1025***	0.0171	0.0086	0.0798	-0.0368***
	(0.0259)	(0.0653)	(0.0551)	(0.1277)	(0.0137)
$PCGDP^2$	-0.0029***	-0.0019	-0.0010	-0.0031	0.0008**
	(0.0008)	(0.0016)	(0.0013)	(0.0030)	(0.0004)
ISLAND	-1.1805***	3.3624***	3.3062***	-0.5271	0.0167
	(0.2212)	(0.7748)	(0.6913)	(1.5924)	(0.0887)
Lag ERROR	1.5173***	5.1216***	3.1786***	7.8569***	0.1347**
	(0.1157)	(0.5479)	(0.4459)	(1.0104)	(0.0674)
N	173	173	173	163	117
R^2	0.8050	0.6246	0.4553	0.5834	0.3554
% Δ in R^2 From Model 1	+34.8	+75.9	+86.1	+13.3	+38.6

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Figures in the parentheses are standard errors.

The only taxa group for which the evidence in support of an Environmental

Kuznets Curve relationship exists is for birds. For vascular plants the EKC relationship

is at odds with prior expectations. The turning point (where per capita GDP has the

maximum impact in terms of species imperilment) comes at a GDP of $17,672 per capita.

Likewise, only two taxa groups show any sensitivity to population density: mammals and

vascular plants. As expected, species imperilment among the vascular plants increases

with increasing human population density. Unexpectedly, however, weakly significant

evidence for increasing human population density association with reduced species

imperilment is found among mammals (model 3). There appears to be no significant

impact of human population density on imperilment of birds, reptiles, or amphibians. In

the absence of the spatial correction term (model 1), a strongly positive impact of

population density on species imperilment is observed for both birds and mammals, in

addition to vascular plants. This suggests that some aspects of population density are

being captured by this spatial dependency measure.

As indicated in previous works (Pandit and Laband 2005; Brown and Laband

2006), a little empirical evidence is found in support of the notion that ecological

benefits, at least in the form of reduced species imperilment, result from concentrations in

the human population. The measure of concentration in the human population is based

on the Gini coefficient, which is assigned a value of 0 for a uniformly-distributed

population and approaches a value of 1 as the population becomes increasingly

concentrated. Coefficient estimates of the GCPOP variable are statistically flat for 4 of

the 5 taxa groups examined (model 3). However, a very sizable and statistically

significant inverse relationship is found between concentration in the human population

and the percentage of endangered amphibians. In a large-scale setting, this finding is consistent with claims made by advocates of the Smart-Growth principle of compact building design. Finally, it is observed that imperilment of both mammals and reptiles is significantly greater on islands than in mainland countries. However, neither amphibians nor vascular plants appear to be characterized by the same vulnerability in this regard. This is rather surprising, since amphibians surely are no more able than reptiles to escape the ravages of exotic invasive species brought to islands by man. By virtue of their immobility, vascular plants are even less able to avoid the impact of anthropogenic change. However, birds are not necessarily island (or country)-bound, so it stands to reason that the island dummy in the bird model would not necessarily, or even likely, be positive.

Beyond simple adjacency, the spatial dependency metrics become increasingly difficult to construct. Thus, even though *a priori* expectation might be that a relatively complex measure, such as the percentage of shared border, conveys more realistic information about the spatial relationship between two countries with respect to species imperilment, it is not clear whether the benefit from constructing the more complex metrics is worth the cost. Table 4.5 presents the R^2 values for otherwise identical spatial error models estimated by using alternative structures of the spatial dependency between countries. Across all of the taxa except mammals, the simple adjacency structure out-performs all of the other metrics, in terms of maximizing model explanatory power. Thus, in this case, there appears not be a trade-off between simplicity and explanatory power.

Table 4.5 R-Square Values for Models with Alternative Structures of the Spatial Error
         Relationship Between Countries

Structures	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Simple adjacency	0.8050	0.6246	0.4553	0.5834	0.3554
2nd order adjacency	0.7471	0.5951	0.3773	0.5733	0.3347
Distance between centroids	0.7171	0.5420	0.3052	0.5170	0.2960
Percent of shared border	0.7958	0.6535	0.4208	0.5683	0.3311

4.3.2 General and Specific Spatial Autocorrelation

In table 4.4 Eq. (4.2) was estimated both with and without controls for spatial autocorrelation, using the SAS Robust Regression weighted least squares technique. Test statistics generated from both spatial error and spatial lag models indicated the presence of significant spatial autocorrelation for every taxa group, across most of the structural specifications: binary contiguity (simple adjacency), higher-order binary contiguity, centroid-to-centroid distance, and percentage of shared border.[5] The question that needs to be addressed now is, what happens to the estimated coefficient on the general spatial autocorrelation term and other explanatory variables when spatial autocorrelation variables that control for specific cross-border effects are introduced in the models? This focus requires further confinement of the analysis based on the lag form of the spatial dependency, which is the formulation employed by McPherson and Nieswiadomy (2005).

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[5] However, the only circumstance that observe statistically significant spatial dependency in models
   involving vascular plants occurs when the dependency is structured as simple adjacency.

To create the aspect-specific cross-border effects, a set of specific (non-binary) contiguity matrices based on data for the four continuous explanatory variables in the model are generated: percent endemic species, human population density, concentration in the human population, and per capita GDP. For example, in the simple adjacency formulation, each country bordering country A was assigned a value equal to that country's population density in the spatial weight matrix.   In the percentage of shared border formulation, each country bordering country A was assigned a value equal to that country's population density, adjusted by the percentage of country A's border that it shares in the spatial weight matrix. In the centroid-to-centroid distance formulation, each country bordering country A was assigned a value equal to that country's population density, adjusted by the Euclidian distance from the center of country A to the center of the bordering country, scaled against the Euclidian distance from the center of country A to the center of the adjacent country with the farthest center point.

SAS Robust Regression weighted least squares procedure (Chen 2002) is then used to estimate models for each taxa group, with alternative configurations of the general and specific spatial lag terms. Similar to previous findings, models with spatial autocorrelation terms based on a simple adjacency dependency structure consistently outperform models based on the other dependency structures, so the estimation results reported in Table 4.6 are for models with this dependency structure (for detailed analysis, see Appendix – IV).

Model 1 in Table 4.4 contains no spatial lag term; model 1 in Table 4.6 contains a general (binary contiguity) spatial lag term only. When comparing model 1 (Table 4.6) against model 1 (Table 4.4), it is quite clear that not only is spatial autocorrelation

consistently a statistically significant aspect of species imperilment measured at the country-level, the generic (unspecified) cross-border effects add considerably to the explanatory power of the taxa-specific models. Model 2 (Table 4.6) results are based on the augmented form of model 1 by new variables that capture specific (non-binary) cross-border effects. Several aspects of this model 2 command attention.

First, the general spatial lag term remains statistically significant across all taxa groups even though certain types of specific cross-border effects are statistically significant in each of the taxa models. Second, consistent evidence is found across taxa groups that the percentage of endemic species in surrounding countries is negatively related to the percent of imperiled species in the referent country, even though the own-country effect of endemic species is positive, as expected. Third, the size of the estimated coefficients on the own-country explanatory variables is affected by inclusion of the specific cross-border dependency variables. For example, there is a sizable increase from model 1 to model 2 with respect to the estimated own-country effect of percent endemic species on percent imperiled species among the birds, mammals and, to a lesser extent, amphibians. More dramatically, the estimated own-country impact of population density on imperilment of mammals changed from positive and statistically significant in model 1 to negative and statistically significant in model 2.

Table 4.6 Simple Adjacency Based Weighted Least Squares Regression Results for
General and Specific Spatial Lags Effect on Species Imperilment

Model 1: Models with General Spatial Lag

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.4433*	8.5747***	2.6200	21.5132***	0.3965
	(0.7691)	(2.7513)	(2.068)	(5.6796)	(0.3900)
PES	0.2948***	0.2666***	0.0085	0.4228***	0.0100***
	(0.0145)	(0.0314)	(0.0148)	(0.0306)	(0.0023)
POPD	-0.0492	3.3128*	-0.2478	-1.7865	0.3192***
	(0.149)	(1.9578)	(0.3929)	(1.0984)	(0.0568)
GCPOP	1.1404	-1.1125	1.7155	-20.2142***	0.0368
	(0.8931)	(3.2367)	(2.4110)	(6.6796)	(0.4681)
PCGDP	0.0439**	0.1769*	0.0480	0.2777*	-0.0315**
	(0.0196)	(0.1006)	(0.0524)	(0.1482)	(0.0135)
$PCGDP^2$	-0.0010**	-0.0058*	-0.0014	-0.0069**	0.0007*
	(0.0005)	(0.0030)	(0.0012)	(0.0035)	(0.0004)
ISLAND	-0.6356***	1.0995	0.9469	-1.8874	-0.0129
	(0.2454)	(0.8487)	(0.6529)	(1.8142)	(0.0896)
SL – General	1.6078***	4.5759***	4.6394***	7.2509***	0.1692**
	(0.1653)	(0.6190)	(0.5557)	(1.201)	(0.0784)
N	173	173	173	163	117
R^2	0.7601	0.5607	0.5203	0.5514	0.3164

Model 2: Models with General and Specific Spatial Lags

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.0480	3.5791	-0.3800	19.2202***	0.8572*
	(0.7102)	(3.4827)	(2.7827)	(7.1702)	(0.4886)
PES	0.5487***	0.3603***	0.0114	0.4943***	0.0096***
	(0.0157)	(0.0368)	(0.0157)	(0.0297)	(0.0023)
POPD	0.0407	-4.2472**	-0.2197	-1.4701	0.2804***
	(0.1177)	(1.8505)	(0.4210)	(1.0094)	(0.0599)
GCPOP	1.5285*	6.9955*	4.4557	-19.0815**	-0.6033
	(0.8269)	(4.0091)	(3.2703)	(8.2546)	(0.5965)
PCGDP	0.0492*	0.1127	0.0939	0.1410	-0.0279*
	(0.0255)	(0.1158)	(0.0637)	(0.1643)	(0.0147)
PCGDP^2	-0.0018**	-0.0052	-0.0015	-0.0036	0.0007*
	(0.0007)	(0.0035)	(0.0013)	(0.0031)	(0.0004)
ISLAND	-0.8031***	0.0968	1.0551	-0.3031	0.0593
	(0.2244)	(0.9151)	(0.7217)	(1.7465)	(0.1084)
SL – General	2.5997***	5.9074***	4.3181***	11.1623***	0.1337*
	(0.2033)	(0.7375)	(0.6175)	(1.3640)	(0.0797)
SL – PES	-3.8992***	-1.9157***	-0.7925*	-5.2580***	-0.0664
	(0.3867)	(0.6470)	(0.4589)	(1.1620)	(0.0833)
SL – POPD	0.7375	6.8741**	0.4557	-8.8494*	-0.2687
	(0.6600)	(2.8874)	(2.2566)	(5.3131)	(0.4817)
SL – GCPOP	-0.1779	-1.1515*	-0.1554	0.4318	0.1582*
	(0.1402)	(0.5951)	(0.4892)	(1.0789)	(0.0888)
SL – PCGDP	0.0012	0.3598	-0.8978**	0.6658	-0.0734
	(0.1364)	(0.5863)	(0.4374)	(1.1233)	(0.0756)
N	173	173	173	163	117
R^2	0.8256	0.6630	0.5451	0.6072	0.3907

Model 3: Models with Specific Spatial Lags only

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.0936	0.4244	-1.7310	12.9975*	0.7958
	(1.2232)	(3.9505)	(3.1686)	(7.8720)	(0.4701)
PES	0.3875***	0.3164***	0.0057	0.4797***	0.0090***
	(0.0254)	(0.0397)	(0.180)	(0.0326)	(0.0022)
POPD	0.6906	-0.1616	-0.0566	-1.2712	0.2783***
	(0.6487)	(0.6708)	(0.4781)	(1.1108)	(0.0575)
GCPOP	1.4608	11.1205**	5.9005	-13.0836	-0.5494
	(1.3897)	(4.6300)	(3.7353)	(9.0582)	(0.5730)
PCGDP	0.0918**	-0.0900	0.1594	0.1897	-0.0283**
	(0.0384)	(0.0992)	(0.0977)	(0.1794)	(0.0141)
PCGDP^2	-0.0026**	-0.0002	-0.0055*	-0.0054	0.0008**
	(0.0011)	(0.0020)	(0.0028)	(0.0034)	(0.0004)
ISLAND	-1.5281***	0.0256	1.6896**	0.3005	0.0851
	(0.3351)	(1.0697)	(0.8202)	(1.9187)	(0.1030)
SL – General	-	-	-	-	-
SL – PES	0.4206	-0.3035	-0.7492	-0.6853	-0.0995
	(0.3818)	(0.7514)	(0.5273)	(1.0322)	(0.0810)
SL – POPD	2.9545***	10.0688***	7.4900***	-0.9067	-0.1300
	(0.9744)	(3.3363)	(2.3349)	(5.7497)	(0.4658)
SL – GCPOP	0.4304**	-0.1262	0.6453	-0.4367	0.1661**
	(0.1987)	(0.6998)	(0.5324)	(1.1921)	(0.0847)
SL – PCGDP	-0.0691	0.3904	-0.9549*	-0.4383	-0.1098
	(0.2010)	(0.6971)	(0.5045)	(1.2358)	(0.0698)
N	173	173	173	163	117
R^2	0.6645	0.4427	0.3743	0.5346	0.3564

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Figures in the parentheses are standard errors.

Similarly, for mammals, the estimated coefficient on the variable reflecting concentration in the human population changed from negative and statistically insignificant in model 1 to positive and statistically significant in model 2. Therefore, while the general control for spatial autocorrelation may be advisable in terms of producing unbiased coefficient estimates of the explanatory variables in the model, inclusion of specific cross-border dependency terms may substantially change the estimated impact of those explanatory variables and thus the interpretations made and policy conclusions drawn. In the present case, this cautionary flag is perhaps most telling with respect to the estimated impact of per capita GDP on species imperilment. Three of the 5 taxa groups in model 1 (birds, mammals, and amphibians) are shown to exhibit a statistically significant Environmental Kuznets Curve: species imperilment rises with PCGDP but with a diminishing effect. However, once the specific spatial dependency terms are added (model 2), the estimated coefficients on PCGDP and PCGDP^2 lose their statistical significance in the mammals and amphibians models.

Finally, while it might be tempting to conjecture *a priori* that controlling for specific cross-border effects will reduce the size of the estimated coefficient on the generic spatial dependency term, the findings suggest that this is not so. In 3 of the 5 cases that are presented, the size of the generic spatial lag term increases in the presence of the specific cross-border effect terms.

In retrospect, this finding makes perfect sense. The generic, binary contiguity spatial lag term aggregates a lot of unspecified cross-border effects, some with a positive impact on species imperilment in the referent country, and others that have a negative impact. In model 2, inclusion of the specific cross-border effects allow to separate out at

least one significant negative effect on species imperilment in a country: the percentage of endemic species in immediately adjacent countries. Compositionally, this must increase the size of the estimated coefficient for the generic spatial lag term, relative to a model (1) with no specific spatial dependency terms included.

The estimation results reported in model 3 include specific cross-border dependency terms but not the general term. It is immediately apparent that the regression R-squared values drop substantially, in most cases, from model 2 to model 3. This not only is consistent with the observation in model 2 that the general spatial lag term was statistically significant in the presence of the specific spatial lag terms across all taxa, it also underscores the relative importance of the general spatial lag in this type of model. In other words, even though it is hard to pin down what they are, cross-border effects loom large with respect to country-level analysis of factors that influence species imperilment.   It is also notable that one or more of the specific cross-border effects that remain "hidden" in the general spatial lag term (model 2) apparently confound the specific effects that can be controlled for. Thus, it is well observable that the sizable positive and statistically significant coefficient estimates on POPD in model 3, for birds and reptiles, disappear when the general spatial lag variable is included in the model (model 2).

4.4 Concluding Remarks

This chapter confirms the advisability, suggested by McPherson and Nieswiadomy (2005), of controlling for spatial autocorrelation in country-level empirical estimation of factors that influence species ecological fragility. Across alternative definitions of the spatial dependency between adjoining countries, the results consistently

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suggest that structuring the econometric specification as spatial error models results in greater explanatory power than spatial lag models for mammals, birds, amphibians, and vascular plants. However, for reptiles the spatial lag structure consistently yields models with greater explanatory power than do the spatial error models. The use of model explanatory power as the criterion for selecting among four alternative definitions of the spatial dependency between countries determined that a simple binary adjacency dummy out-performs higher-order adjacency, Euclidean distance between centroid points of adjoining countries, and percentage of shared border. This suggests that the old maxim "Keep It Simple, Stupid" (KISS) should suffice for empirical researchers interested controlling for spatial autocorrelation when estimating the determinants of species imperilment at a country-level of analysis.

It has been acknowledged that the results are a bit unsatisfying in at least one respect: interpretation. Since inclusion of the simple adjacency-based spatial error term resulted in population density losing its statistical significance as an explanatory variable in model with no control for spatial dependency, some aspect of the spatial dependency must be related to similarities in population density across neighboring countries. Controlling for spatial autocorrelation at least helps reduce the impact of a dependency-related omitted variable problem. But it is not a panacea since it does not reveal the nature of the dependency in terms of variables that the researchers might actually be interested in.

In a variety of contexts, empirical analyses that focus on counties, states, or countries probably are subject to cross-border effects, for which the conventional adjustment is the inclusion of a single spatial autocorrelation term that aggregates a

potentially large set of contributory factors. By extending the earlier effort, discussed in

this chapter, to capture spatial effects on empirical analyses, it has been demonstrated that

it is possible, indeed it may be quite desirable, to include control variables that capture

specific cross-border effects in addition to the generic control for spatial autocorrelation.

In at least some cases, models that contain more meticulous controls for spatial

dependency exhibit substantially enhanced explanatory power as compared to otherwise

equivalent models that contain a single spatial lag variable based on a simple binary

contiguity weights matrix.   In part, this enhanced explanatory power reflects quite

different coefficient estimates for critical explanatory variables between the former

models and the latter ones. Thus, researchers interested in the effects of specific

explanatory variables on the dependent variable under consideration may find that

estimates of the explanatory variable(s) in question may be rather sensitive to whether

specific spatial dependency effects have been controlled for. At a minimum, this should

give researchers who use data characterized by spatial autocorrelation reason to be

cautious about the conclusions they draw from their empirical estimates.

There is no doubt that not all spatial dependency is created equal. That is, cross-

border externalities likely loom larger in some contexts than in others. Therefore,

exercise of a little common sense is in order when considering the desirability of going

the extra mile to control for specific spatial dependencies. From an analytical standpoint,

if inclusion of a general spatial lag variable substantially increases the model R-square

value, then further exploration of the impact of specific spatial dependencies on

coefficient estimates seems worthwhile. On the other hand, even if a general spatial lag

term is statistically significant, if it adds only slightly to the overall explanatory power of

a model, it seems doubtful that inclusion of specific spatial dependency terms will lead to significantly different coefficient estimates.

There are a growing interest and continuing debate among policy makers and scientific community about a potential direct link of economic freedom and corruption to environmental degradation. Using the best spatial model and dependency structure identified in this chapter, the empirical link of economic freedom and corruption to species imperilment is explored in the next chapter to shed some lights on this growing concern.

CHAPTER 5

ECONOMIC FREEDOM, CORRUPTION, AND SPECIES IMPERILMENT

5.1 Introduction

Economic freedom and corruption perceptions indices have been widely used in the

economic growth literature, as researchers investigate possible linkages between these

indices and the distribution of economic performance across countries. The empirical

literature is divided on the effect of economic freedom and corruption on economic

growth. One strand of this literature suggests a positive and significant relationship

between a country's economic freedom and its economic growth (de Vanssay and

Spindler 1994; Easton and Walker 1997; Wu and Davis 1999; Hanson 2000; Ali and

Crain 2002; Carlsson and Lundstrom 2002; Pitlik 2002). Others suggest that this

relationship is insignificant (Gwartney, Lawson, and Holcombe 1999; de Haan and Sturm

2000; Heckelman and Stroup 2000; Adkins, Moomaw, and Savvides 2002) for all

measures of economic freedom (de Haan and Siermann 1998). Similarly, most of the

empirical research that focuses on possible linkages between corruption and economic

growth identifies a negative relationship, arguing that higher levels of corruption

significantly hinder economic growth (Mauro 1995; Brunetti 1997; Li, Xu, and Zou

2000; Mo 2001; Gyimah-Brempong 2002; Méon and Sekkat 2005). However, there is

evidence to suggest that the negative effect of corruption on growth is not a rule

(Pellegrini and Gerlagh 2004) and that in some cases, the effect is even significantly

positive (Barreto 2001; Rock and Bonnett 2004).

Another strand of literature, commonly known as the Environmental Kuznets Curve (EKC) literature, has been developed by researchers attempting to understand possible linkages between environmental degradation in a country and measures of economic performance. In theory, desperately poor people are willing to despoil their local environment in order to improve their economic circumstances. However, beyond some threshold level of economic well-being, environmental quality becomes a normal good, i.e., demand for it increases with increasing income. This suggests an inverted U-shaped relationship between economic growth in terms of per capita income and various (specific) indicators of environmental degradation (Grossman and Krueger 1995; Torras and Boyce 1998; Barrett and Graddy 2000), although the relationship also has been described as N-shaped (Grossman and Krueger 1995; Torras and Boyce 1998).

Using different measures of environmental degradation such as air pollution (Selden and Song 1994; Grossman and Krueger 1995; Torras and Boyce 1998; Cole, Rayner, and Bates 2001), water pollution (Shafik 1994; Grossman and Krueger 1995; Torras and Boyce 1998), deforestation (Panayotou 1993), and ecologically imperiled species (McPherson and Nieswiadomy 2005), researchers have presented empirical evidence in support of EKC relationships. However, recent reviews of the EKC literature have raised questions about the existence of an EKC for specific forms of environmental degradation (Borghesi 1999; Meyer, van Kooten, and Wang 2003; Stern 2004). Skeptics of EKC relationships argue that the EKC is an artifact of (1) technological/structural change in production and associated impacts on indicators of environmental degradation (de Bruyn, van den Bergh, and Opschoor 1998) and (2) specialization in production and

trade of goods and services across the nations that permits richer nations to "export" environmental degradation to poorer countries (Arrow et al. 1995; Stern, Common, and Barbier 1996). In addition, the lack of econometric rigor, particularly the tests for some statistical properties such as variable distribution, serial correlation (in time series data), model adequacy and specification tests, has raised concerns about earlier EKC studies (Stern 2004).

This chapter weaves these two strands of the scientific literature together based on the proposition that economic freedom and corruption are linked to economic prosperity and that economic prosperity is related to environmental degradation. The empirical question explored in the chapter is whether economic freedom and corruption are linked, albeit perhaps indirectly through economic prosperity, to environmental degradation. Using data from 152 countries, taxa specific models of factors that influence species imperilment are estimated by controlling for cross-border effects. The results suggest that across several taxa groups there is a statistically significant relationship between economic freedom and species imperilment. However, consistent evidence of a similar relationship between corruption and species imperilment is observed for only one taxa group. The chapter is organized as follows: Section 2 reviews the literature that focuses on possible linkages between economic freedom/corruption and environmental degradation. The estimating model, variables, and data are discussed in section 3. Model results and discussion are reported in section 4. Section 5 contains the concluding remarks.

5.2 Linking Economic Freedom and Corruption to Environmental Degradation

Explaining the indirect linkage between economic freedom and the environment,

Jerry Taylor of the Cato Institute argues the following:

> Economic liberalization leads to economic growth, which in turn generates new
> economic opportunities and sources of livelihood, thereby alleviating poverty and
> reducing pressures on the environment (Taylor 2002).

Typically, the corruption-environment linkage is expressed as an indirect relationship. The usual linkage is that corruption leads to poverty (Crystalclearforum 2006) and that the poverty trap will cause more harm to the environment. However, a more direct linkage is possible, with similar adverse environmental consequences, as argued by Peter Eigen, the then Chair of Transparency International (TI):

> Corrupt political elites in the developing world, working hand-in-hand with
> greedy business people and unscrupulous investors, are putting private gain
> before the welfare of citizens and the economic development of their countries.
> From illegal logging to blood diamonds, we are seeing the plundering of the earth
> and its people in an unsustainable way (TI 2002).

Scientific discussion of linkages between economic freedom and/or corruption perceptions indices and environmental degradation is just gaining traction. Early on, Lopez and Mitra (2000) argued that corruption and lobbying by vested interests are important sources of environmental degradation in developing countries. More recently, Lundstrom (2003) discussed the effect of specific economic freedom categories on both economic growth and the environment and highlights some important considerations for empirical work. Carlsson and Lundstrom (2003) conducted a cross-country analysis of the impact of economic and political freedom on CO_2 emissions at the cross-country level. They found that certain constituent categories of freedom that are used in the

calculation of the overall Transparency International ratings are significantly related to CO_2 emissions while others are not. In their empirical study of corruption, democracy, and environmental policy, Pellegrini and Gerlagh (2005) found that corruption is an important determinant of environmental policy stringency. The less corrupt the country is, the more stringent the environmental policies are, and vice versa.

With the lone exception of McPherson and Nieswiadomy (2005), all other cross-country analyses considered local (within-country) effects only while ignoring the possibility of spillover effects. However, spillover effects are extremely important in terms of correctly measuring the extent of environmental degradation (e.g., air pollution, water pollution, and species imperilment), which is trans-boundary in nature and has both local and global effects. For example, a Gobi desert storm that originates in central China and Mongolia travels through Europe and sometimes lands in the eastern U.S., carrying air pollutants all along the way (Barta 2006). Thus, such a storm affects northern Atlantic plant species. Likewise, air pollution in Mexico is not confined within Mexico's political boundaries, and deforestation in the Brazilian Amazon affects not only the species dynamics within Brazil but those of its neighbors as well. As a corollary, the environmental policies a particular country implements might well have an impact on its neighbors. For example, if a particular country implements programs to reduce river pollution, the program impact is shared to some extent with down-stream countries as well.

Consequently, if cross-border effects are not integrated into the analysis, empirical investigation of possible linkages between economic growth and environmental degradation may significantly mis-measure the size and significance of relationships. So,

the absence of controls for spatial dependency in earlier cross-country studies may suggest an omitted variable bias. In the previous chapters dealing with cross-country analyses of species imperilment, it is consistently determined that spatial dependency across countries is highly significant and needs to be controlled for. Depending on the nature of environmental degradation and its mode of spread and extent, different mechanisms (adjacency structures) to specify the spatial dependency effect can be argued; however, for species imperilment, a simple adjacency dummy variable that reflects general but unspecified spatial dependency was found to be superior to alternatives (Pandit and Laband 2007a). In an extensive investigation of spatial dependency in models of species imperilment presented in chapter 4, it is found that a single, simple adjacency structure of spatial dependency across countries may out-perform other specific measures of adjacency specifications.[6]

5.3 Models, Data, and Methods

In a cross-country context, a number of factors, both natural and anthropogenic, that influence species' ecological imperilment have been confirmed empirically by previous researchers (Naidoo and Adamowicz 2001; McPherson and Nieswiadomy 2005; Pandit and Laband 2007a). These include species endemism, human population density, the spatial distribution of the human population, economic conditions (per capita income), and special geographic considerations. The model of species imperilment

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[6] In earlier chapters, it is found that for all taxa, spatial dependency was present for all form of dependency: simple, higher order, centroid distance, and shared border. Among these, it is noted that a simple binary adjacency structure (countries that share a common border are assigned a value of 1 in the adjacency matrix and otherwise 0) is superior to other forms and that the spatial error models out-perform dependent, variable-based lag models for almost all taxa.

proposed in the chapter 4 is augmented by incorporating economic freedom and

corruption perceptions indices as explanatory variables:

$$PIS_{ij} = \beta_0 + \beta_1 \, PES_{ij} + \beta_2 \, POPD_i + \beta_3 \, GCPOP_i + \beta_4 \, EFI_i + \beta_5 \, EFI^2 +$$
$$\beta_6 \, ISLAND_i + \beta_7 \, LAG\,\varepsilon_{ij} + v_{ij}, \tag{5.1}$$

$$PIS_{ij} = \beta_0 + \beta_1 \, PES_{ij} + \beta_2 \, POPD_i + \beta_3 \, GCPOP_i + \beta_4 \, CPI_i + \beta_5 \, CPI^2 +$$
$$\beta_6 \, ISLAND_i + \beta_7 \, LAG\,\varepsilon_{ij} + \xi_{ij}, \tag{5.2}$$

where for each country, PIS_{ij} = the percentage of species in taxa j from country i that

were on the World Conservation Union's (IUCN) Red List of threatened species in 2004,

PES = the percent of endemic species, POPD = population density (thousand persons per

square kilometer), GCPOP = a Gini Coefficient Index for population distribution, EFI =

Index of Economic Freedom and CPI = Corruption Perceptions Index, ISLAND = a

dummy variable (1 = island, 0 = mainland), ε_{ij} = the ordinary regression error terms for

each taxa for both economic freedom and corruption models, LAG ε_{ij} = spatial error lag

terms, and v_{ij} and ξ_{ij} are the weighted least square error terms for economic freedom and

corruption models for each taxa, respectively. Deviating from models of earlier chapters

and focusing on the specific effect of economic freedom and corruption on species

imperilment, per capita income variable is excluded in these regression models due to its

high collinearity with economic freedom[7] and corruption[8] indices.

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[7] The correlation between EFI and per capita income is -0.73602 (for birds, mammals, and reptiles),
-0.74216 (amphibians), and -0.77296 (vascular plants).

[8] The correlation coefficient between CPI and per capita income is 0.86988 (for birds, mammals, and
reptiles), 0.86916 (amphibians), and 0.89718 (vascular plants). The negative (positive) correlation of

5.3.1 Economic Freedom Index (EFI)

The economic freedom index is a composite index that characterizes the degree to which an economy is a market economy (Berggren 2003), in which the central components are voluntary exchange, free competition, and protection of persons and property (Gwartney and Lawson 2004). Economic theory suggests that such freedom affects incentives, productive efforts, the effectiveness of resource use (de Haan and Sturm 2000), and, consequently, economic growth of a country. It is the most reliable and consistent determinant of economic growth, which in turn alleviates poverty (Pasicolan and Fitzgerald 2002). Empirical researchers have used one of the economic freedom indices produced by the Frasier Institute (Gwartney and Lawson 2004), Scully-Slottje (de Vanssay and Spindler 1994; de Haan and Siermann 1998) or the Heritage Foundation/*Wall Street Journal* to describe the relationship between economic freedom and economic growth. In this analysis, the index developed by the Heritage Foundation /*Wall Street Journal* is used to explore the link between EFI and species imperilment. The Heritage Foundation computes the EFI as a simple average score of 10 major policy factors[9] characterized by 50 key economic indicators of a country. Scores range from 1 (economically free) to 5 (economically suppressed). Lower EFI scores mean greater economic freedom in a country, and vice versa.

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percent imperiled species with EFI (CPI) is mainly due to scaling measure used by Heritage Foundation (Transparency International) in reporting their data.

[9] These factors include trade policy, fiscal burden of government, government intervention in the economy, monetary policy, capital flows and foreign investment, banking and finance, wages and prices, property rights, level of regulation, and black market activity.

5.3.2 Corruption Perceptions Index (CPI)

The CPI defines corruption as the abuse of public office for private gain and measures the degree to which corruption is perceived to exist among a country's public officials and politicians. It is a composite index based on 16 opinion surveys[10] of business people and country analysts gathered by 10 independent institutions[11]. All sources employ a homogeneous definition of "extent of corruption" in a country. Since 1995, Transparency International (TI) has published the index annually. The CPI scores range from 10 (highly clean) to 0 (highly corrupt). TI uses a score of 5.0 as a threshold level that distinguishes serious corruption in a country.

Data on threatened and endemic species were taken from the EarthTrends Environmental Portal of the World Resources Institute (WRI 2004). Human population data were obtained from the United Nations Population Division (UNPD 2004). Following Damagaared and Weiner (2000) and Dixon et al. (1987), a Gini Coefficient index is derived to measure the spatial concentration of the human population in each country. The index values range from 0, which reflects a uniform distribution of the population, to 1, which means that a country's population is concentrated in a single location. It was derived from a LandScan 2002 gridded population distribution map developed by Oak Ridge National Laboratory. An island dummy variable identified

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[10] At least 3 surveys are required for a country to be included in CPI ranking. The detailed survey methodology is found in Lambsdorff (2005).

[11] 10 institutions include Columbia University, the Economists Intelligence Unit, Freedom House, Information International from Beirut (Lebanon), the International Institute for Management Development (in Lausanne), the Merchant International Group Limited (London), the Political and Economic Risk Consultancy (in Hong Kong), the United Nations Economic Commission for Africa, the World Economic Forum, and the World Markets Research Centre (in London).

the nations that are geographically isolated (CIA 2004).

A two-step modeling approach is used to document the effect of economic freedom and corruption on species imperilment for taxa-level data on mammals, birds, reptiles, amphibians, and vascular plants. First, errors (ε_{ij}) for each model are estimated (with no spatial dependency term included). Then, using the insights from the findings of chapter 4, a simple adjacency spatial error lag term, LAGε_{ij} for each country is constructed by taking the average of the errors of adjacent countries. This spatial error lag term was included in the spatial error lag models as an explanatory variable to capture unspecified cross-border effects on species imperilment models. Secondly, following the same approach as in error lag construction, a dependent variable-based general spatial lag term is constructed for each model to capture the aggregate effect of all explanatory variables in the model. This general spatial lag term was then included in the general spatial lag models, replacing error lag term of error models. A spatial dependency weights matrix for each of the explanatory variables is also created, averaging the values for all bordering countries. This captures cross-border effects in terms of economic freedom or population density of neighboring countries on species imperilment in the referent country, for example, rather than forcing all effects into a single variable that is difficult to interpret. Then both general and specific spatial lag terms are included as additional explanatory variables in the third set of models. Finally, the level and squared terms for both EFI and CPI are introduced in the models to observe the structure of the relationship between species imperilment and EFI/CPI. Both EFI and CPI are treated as continuous variables (EFI and CPI are measured to two and one decimals, respectively). The exploratory analysis of the data indicated non-constant error variance

(heteroskedasticity), so the model is estimated using the SAS Robust Regression weighted least squares technique.

It is expected that the percentage of imperiled species in a country is directly related to the percentage of endemic species, population density, and corruption in that country and inversely to the Gini Coefficient for population distribution and economic freedom. In addition, islands are expected to have more ecologically fragile species than mainland countries by virtue of their geographic isolation and sensitivity of flora and fauna to introduction of invasive species (Czech, Krausman, and Devers 2000).

5.4 Results and Discussion

Table 5.1 shows the sample statistics. Among the taxa groups in the sample, amphibians are the most imperiled (about 16%) and have the highest rate of endemism (about 17%), whereas vascular plants and birds are the least imperiled (about 1%) and have the lowest rate of endemism (about 3%). Depending on the number of countries covered in each taxa model, mean population density ranges from 158 to188 persons /km^2, with Mongolia (2 persons/km^2) and Singapore (6,959 persons/km^2) being the most sparsely and densely populated countries, respectively. Similarly, the mean value of the Gini coefficient index for population dispersion (0.88) suggests that most countries have relatively highly concentrated human populations. Singapore (0.59) has the most evenly-distributed population, whereas Mongolia (0.999) has its population concentrated in only a few locations.

The EFI mean score of 3.0 suggests that, on average, the countries included in the analysis are at the lower margin of the "mostly unfree" (3.00 to 3.95) category, specified as such by the Heritage Foundation/*Wall Street Journal*. The 2005 EFI data reveal that

Luxemburg (score 1.63) is the most economically free country, whereas North Korea (score 5.00) is the most economically suppressed country. Among countries in the sample, the average CPI score ranges from 4.1 to 4.3 for all 5 taxa, indicating that in general, most countries are ruled by corrupt regimes. TI's classification suggests that a score of 5.0 is the borderline to distinguish countries that fall on the relatively corrupt or clean regime (< 5.0 corrupt and > 5.0 clean). The CPI score indicates that Iceland (9.7) is the world's least corrupt country, whereas Bangladesh (1.7) and Chad (1.7) are perceived as the most corrupt.

A graphical depiction of the relationship of economic freedom and corruption with species imperilment is given in Figures 5.1 and 5.2, respectively. It seems difficult to ascertain the specific nature of the species imperilment relationship with economic freedom and corruption for each taxon from these figures. However, it is apparent that there are some outlying EFI and CPI observations for each of the imperiled species group.

Weighted Least Squares regression results for the taxa-specific model estimations, including spatial error and spatial lag dependency structures, are presented in Tables 5.2a-e for both EFI and CPI. As expected, the percentage of imperiled species in a country is positively and strongly influenced by the percentage of endemic species in that country. Excepting the reptiles, this finding is consistent across all taxa groups for both EFI and CPI based models.

Table 5.1 Sample Statistics[12]

Variable		Birds	Mammals	Reptiles	Amphibians	Vascular Plants
PIS	Mean	3.343 (3.420)	9.501 (9.628)	4.245 (4.306)	11.425 (11.849)	1.159 (1.372)
	Std. dev.	2.729 (2.724)	5.289 (5.383)	5.033 (5.025)	17.587 (17.911)	2.096 (2.723)
	Min.	0.000	0.000	0.000	0.000	0.000
	Max.	21.083	33.333	36.364	97.872	11.600 (18.000)
PES	Mean	3.212 (3.391)	4.352 (4.581)	11.048 (10.929)	15.723 (16.484)	13.602 (14.685)
	Std. dev.	7.619 (7.738)	9.310 (9.481)	17.442 (17.118)	23.559 (24.514)	18.373 (19.517)
	Min.	0.000	0.000	0.000	0.000	0.000 (0.033)
	Max.	45.476	61.818	90.741	89.381 (91.667)	89.999
POPD	Mean	158.121 (161.324)	158.121 (161.324)	158.121 (161.324)	160.218 (163.224)	182.134 (188.180)
	Std. dev.	583.446 (587.176)	583.446 (587.176)	583.446 (587.176)	591.118 (592.265)	697.118 (710.771)
	Min.	1.679	1.679	1.679	1.679	1.679
	Max.	6959.677	6959.677	6959.677	6959.677	6959.677
GCPOP	Mean	0.880 (0.881)	0.880 (0.881)	0.880 (0.881)	0.878 (0.879)	0.871 (0.877)
	Std. dev.	0.095 (0.094)	0.095 (0.094)	0.095 (0.094)	0.095 (0.093)	0.099 (0.095)
	Min.	0.590	0.590	0.590	0.590	0.590
	Max.	0.999	0.999	0.999	0.999	0.999

Table 5.1 Sample Statistics[12] (Cont'd)

Variable		Birds	Mammals	Reptiles	Amphibians	Vascular Plants
EFI	Mean	3.010	3.010	3.010	3.018	2.996
	Std. dev.	0.685	0.685	0.685	0.687	0.680
	Min.	1.600	1.600	1.600	1.600	1.600
	Max.	4.600	4.600	4.600	4.600	4.600
CPI	Mean	4.132	4.132	4.132	4.078	4.266
	Std. dev.	2.183	2.183	2.183	2.151	2.318
	Min.	1.700	1.700	1.700	1.700	1.800
	Max.	9.700	9.700	9.700	9.600	9.700
ISLAND	Mean	0.164 (0.167)	0.164 (0.167)	0.164 (0.167)	0.155 (0.163)	0.206 (0.204)
	Std. dev.	0.372 (0.374)	0.372 (0.374)	0.372 (0.374)	0.364 (0.371)	0.406 (0.405)
	Min.	0.000	0.000	0.000	0.000	0.000
	Max.	1.000	1.000	1.000	1.000	1.000
N		152 (150)	152 (150)	152 (150)	148 (147)	102 (98)

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[12] Statistics for both economic freedom and corruption based models for all 5 taxa are presented. Parentheses denote the statistics for corruption wherever it is different from economic freedom.

Figure 5.1 Relationship between Economic Freedom and Percent Imperiled Species by Taxa
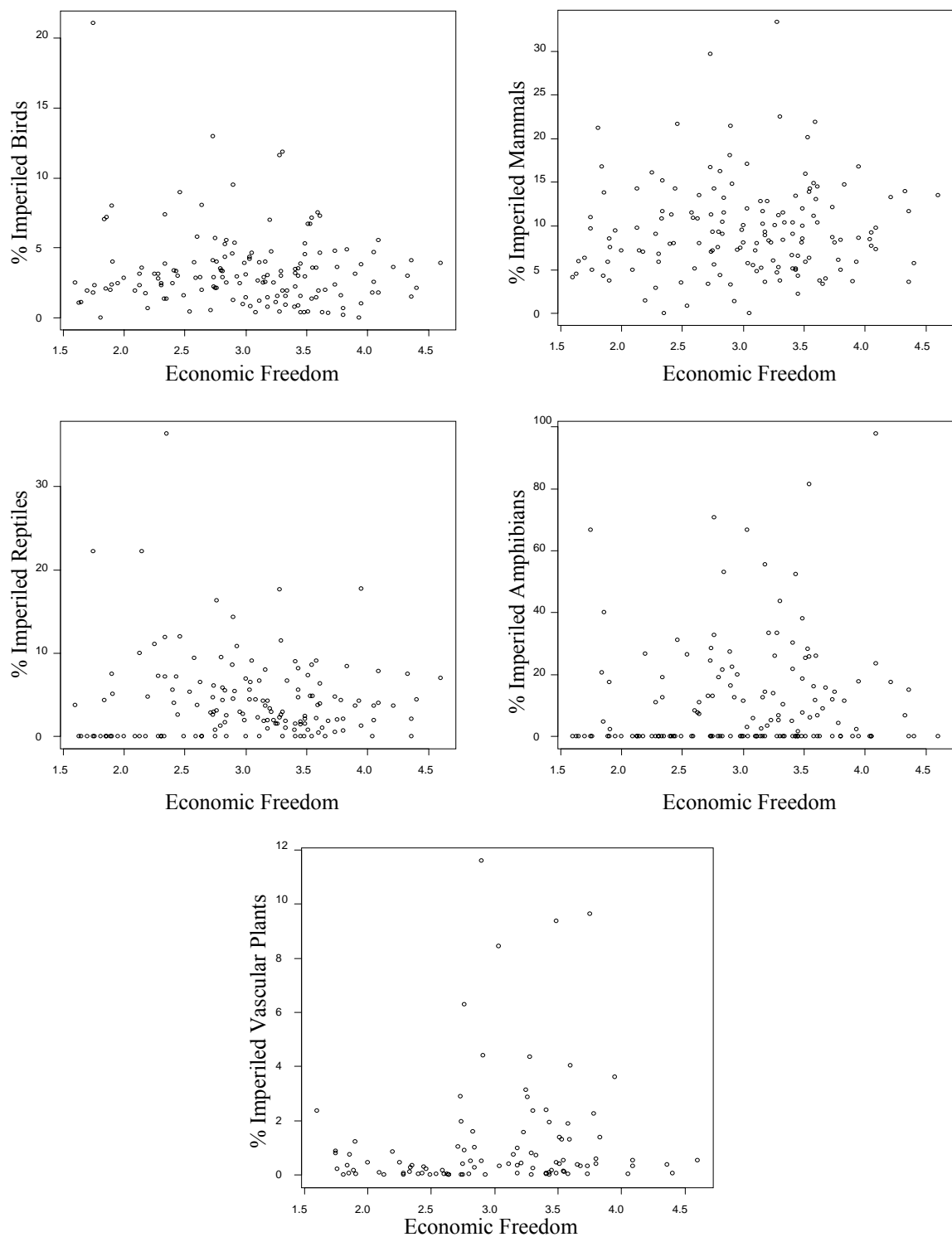
Figure 5.2 Relationship between Corruption and Percent Imperiled Species by Taxa

Table 5.2a Regression Results for Economic Freedom, Corruption, and Species Imperilment - Birds

Variables	Economic Freedom Index (EFI)			Corruption Perception Index (CPI)		
	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model
Constant	-2.0597 (1.5484)	-1.2836 (1.6861)	-3.4976** (1.6386)	-1.4710* (0.8030)	0.0058 (0.9178)	-0.4591 (0.9217)
PEB	0.3616*** (0.0237)	0.2765*** (0.0157)	0.5198*** (0.0191)	0.3332*** (0.0183)	0.2765*** (0.0154)	0.5499*** (0.019)
POPD	0.1625 (0.1438)	0.0646 (0.1554)	-0.0519 (0.1300)	0.1485 (0.1409)	0.0866 (0.1540)	0.1826 (0.1326)
GCPOP	2.2176*** (0.8561)	1.3114 (0.9853)	2.3420** (1.0108)	2.3362*** (0.8588)	1.2715 (0.9864)	2.5088** (1.0244)
INDEX	1.6861** (0.8531)	1.8379** (0.9246)	2.1383*** (0.8059)	0.7824*** (0.1892)	0.7430*** (0.2071)	0.0250 (0.1719)
INDEX^2	-0.2908** (0.1407)	-0.2942** (0.1526)	-0.3388*** (0.1264)	-0.0709*** (0.0175)	-0.0705*** (0.0191)	-0.0113 (0.0154)
ISLAND	-0.6706** (0.2741)	-0.4006 (0.2890)	0.7796*** (0.2871)	-0.5585** (0.2653)	-0.5046* (0.2918)	-0.9271*** (0.297)
Lag ERROR	1.5768*** (0.1343)			1.5678*** (0.1259)		
Spatial Lag		1.7204*** (0.1721)	2.4324*** (0.2053)		1.6197*** (0.1672)	2.3509*** (0.197)
Lag – PEB			-3.7652*** (0.3845)			-4.0141*** (0.392)
Lag - POPD			1.6552** (0.6683)			1.0741 (0.7142)
Lag - GCPOP			-0.1056 (0.1339)			-0.1370 (0.1438)
Lag –INDEX			0.1054 (0.1310)			0.1380 (0.1501)
N	152	152	152	150	150	150
R^2	0.7776	0.7447	0.8211	0.7692	0.7465	0.8233

***, **, * - - statistical significant at the 0.01, 0.05, and 0.10 levels, respectively.

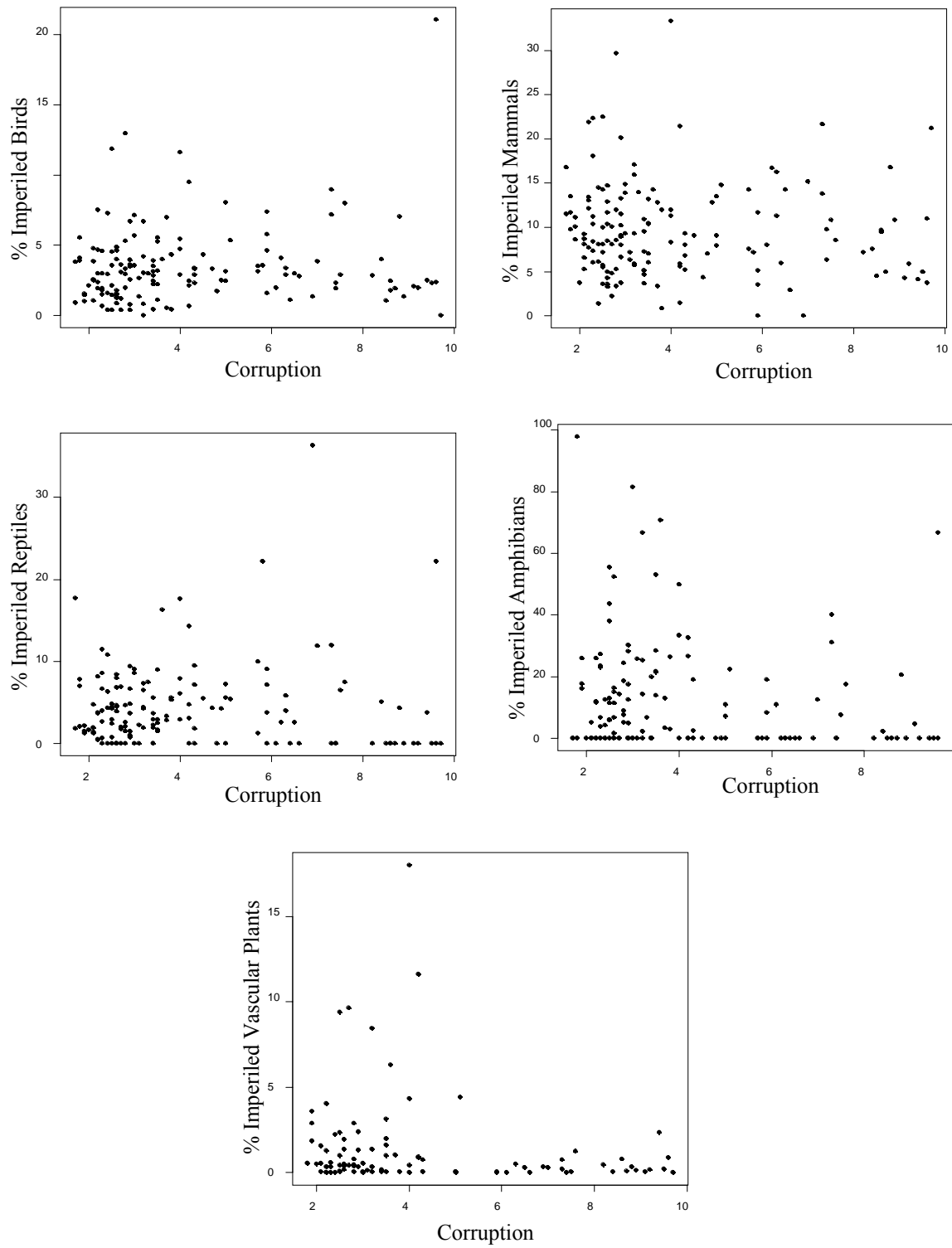Figures in the parentheses are standard errors.

Table 5.2b Regression Results for Economic Freedom, Corruption, and Species Imperilment - Mammals

Variables	Economic Freedom Index (EFI)			Corruption Perception Index (CPI)		
	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model
Constant	-9.2535* (4.8399)	-1.5453 (5.2567)	-11.9049** (5.6142)	5.7454** (2.7150)	4.6191 (2.9117)	0.1382 (3.6927)
PEM	0.2752*** (0.0322)	0.2762*** (0.0355)	0.2928*** (0.0306)	0.3251*** (0.0344)	0.2345*** (0.0329)	0.3467*** (0.0364)
POPD	-0.5559 (0.4537)	3.1358 (1.9267)	-0.4222 (0.4452)	-0.5783 (0.4878)	8.1270*** (2.9208)	-0.2213 (0.5487)
GCPOP	4.7517* (2.6385)	0.6517 (2.9812)	4.2061 (3.4127)	2.5202 (2.9249)	2.1234 (3.1803)	9.2278** (4.0899)
INDEX	8.1415*** (2.6793)	5.9052** (2.8990)	10.8459*** (2.8080)	0.0252 (0.6532)	0.6491 (0.7036)	0.1407 (0.6797)
INDEX^2	-1.2361*** (0.4417)	-0.9549** (0.4790)	-1.6538*** (0.4420)	-0.0217 (0.0603)	-0.0731 (0.0643)	-0.0191 (0.0636)
ISLAND	4.2023*** (0.8247)	2.7342*** (0.9663)	2.7526*** (0.8421)	1.9577** (0.9039)	1.8608* (1.0446)	-0.4711 (0.9732)
Lag ERROR	4.8669*** (0.5114)			4.9857*** (0.5455)		
Spatial Lag		3.6092*** (0.5161)	4.3891*** (0.4936)		3.5578*** (0.4923)	4.6257*** (0.563)
Lag – PEM			-3.5969*** (0.5948)			-2.0528*** (0.6133)
Lag - POPD			6.3208*** (2.3251)			2.9260 (2.8076)
Lag - GCPOP			0.2603 (0.4433)			-1.1778** (0.5588)
Lag –INDEX			-0.1088 (0.4611)			-0.0474 (0.6012)
N	152	152	152	150	150	150
R^2	0.6640	0.5510	0.6885	0.6534	0.5673	0.6696

***, **, * - - statistical significant at the 0.01, 0.05, and 0.10 levels, respectively.

Figures in the parentheses are standard errors.

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Table 5.2c Regression Results for Economic Freedom, Corruption, and Species Imperilment - Reptiles

Variables	Economic Freedom Index (EFI)			Corruption Perception Index (CPI)		
	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model
Constant	-4.7462 (4.3351)	-4.2728 (4.0192)	-7.3698 (5.1059)	0.9209 (2.2054)	-0.3085 (2.1563)	-3.3766 (2.8980)
PER	0.0066 (0.0147)	0.0027 (0.0137)	0.0111 (0.0152)	0.0091 (0.0141)	0.0091 (0.0140)	0.0137 (0.0153)
POPD	-0.1130 (0.3923)	0.2011 (0.3653)	0.2971 (0.4101)	0.2096 (0.3754)	0.2641 (0.3724)	0.4357 (0.4219)
GCPOP	3.4052 (2.3144)	2.5045 (2.1623)	6.2603** (3.1495)	2.4180 (2.3002)	2.9845 (2.2717)	6.4908** (3.2092)
INDEX	3.9986* (2.3011)	3.8225* (2.1410)	3.6726 (2.5161)	0.7419 (0.5052)	0.8250 (0.5028)	0.8475 (0.5238)
$INDEX^2$	-0.6349* (0.3772)	-0.6023* (0.3511)	-0.5849 (0.3975)	-0.0869* (0.0464)	-0.0937** (0.0461)	-0.0985 (0.0484)
ISLAND	0.4736 (0.7486)	0.0580 (0.7107)	0.3214 (0.7886)	0.0230 (0.8639)	0.3630 (0.6748)	0.3205 (0.7568)
Lag ERROR	4.6658*** (0.5561)			4.3937*** (0.5252)		
Spatial Lag		4.0295*** (0.4376)	3.6518*** (0.5027)		3.7796*** (0.4458)	3.2997*** (0.5072)
Lag – PER			-0.5393 (0.4481)			-0.7406* (0.4392)
Lag - POPD			1.3093 (2.2266)			1.5975 (2.3147)
Lag - GCPOP			-0.3888 (0.4186)			-0.1935 (0.4486)
Lag –INDEX			0.3114 (0.4015)			0.2420 (0.4594)
N	152	152	152	150	150	150
R^2	0.5292	0.5474	0.5736	0.5512	0.5490	0.5558

***, **, * - - statistical significant at the 0.01, 0.05, and 0.10 levels, respectively.

Figures in the parentheses are standard errors.

Table 5.2d Regression Results for Economic Freedom, Corruption, and Species Imperilment - Amphibians

Variables	Economic Freedom Index (EFI)			Corruption Perception Index (CPI)		
	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model
Constant	3.3119 (9.7678)	10.4936* (5.7436)	5.6447 (12.5598)	7.8376 (5.7889)	10.7706 (10.5357)	10.8401 (7.0068)
PEA	0.4919** (0.0284)	0.4749*** (0.0287)	0.5189*** (0.0310)	0.4821*** (0.0276)	0.4601 (0.0154)	0.5164*** (0.0284)
POPD	-0.5838 (0.9024)	-0.8600 (0.9943)	-0.2410 (1.0231)	-0.0534 (0.9977)	-0.8439 (0.9568)	-0.3464 (1.0503)
GCPOP	-9.9815* (5.3646)	-14.6106** (6.0221)	-14.3796* (7.8571)	-8.0431 (6.0670)	-11.6699** (5.6820)	-14.2055* (7.6711)
INDEX	5.8789 (5.4595)	2.7483** (1.3999)	6.4556 (6.4045)	1.6333 (1.4501)	3.3946 (5.8329)	1.9855 (1.3384)
INDEX^2	-0.9330 (0.8988)	-0.2268* (0.1303)	-1.0379 (1.0094)	-0.1699 (0.1342)	-0.7408 (0.9561)	-0.1872 (0.1280)
ISLAND	-1.9056 (1.7948)	-3.3875* (1.9187)	-3.1316 (1.9350)	-3.6044* (1.9331)	-2.8348 (1.8832)	-2.6324 (1.8857)
Lag ERROR	7.0490** (0.9938)			7.4870*** (1.0442)		
Spatial Lag		6.5159*** (1.0196)	9.2941*** (1.2740)		5.0564*** (0.9941)	10.4569*** (1.228)
Lag – PEA			-5.1486*** (1.0847)			-5.4188*** (1.0839)
Lag - POPD			-8.6366* (5.0848)			-9.8394* (5.1404)
Lag - GCPOP			1.0277 (0.9872)			0.4693 (1.0526)
Lag –INDEX			-1.5381 (1.0039)			0.9872 (1.1455)
N	148	148	148	147	147	147
R^2	0.6273	0.6015	0.6454	0.6312	0.6015	0.6640

***, **, * - - statistical significant at the 0.01, 0.05, and 0.10 levels, respectively.

Figures in the parentheses are standard errors.

Table 5.2e Regression Results for Economic Freedom, Corruption, and Species Imperilment - Vascular Plants

Variables	Economic Freedom Index (EFI)			Corruption Perception Index (CPI)		
	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model	Spatial Error Model	General Spatial Lag Model	General and Specific Spatial Lag Model
Constant	0.2259 (0.8395)	0.5949 (0.8264)	1.5850 (0.9762)	0.5456 (0.5470)	0.5555 (0.5043)	1.9114*** (0.6226)
PEVP	0.0126*** (0.0026)	0.0121*** (0.0025)	0.0113*** (0.0025)	0.0117*** (0.0028)	0.0120*** (0.0026)	0.0181*** (0.0028)
POPD	0.3330*** (0.0631)	0.3207*** (0.0613)	0.2699*** (0.0665)	0.3549*** (0.0685)	0.3417*** (0.0629)	0.2370*** (0.0717)
GCPOP	-0.2304 (0.4868)	-0.3197 (0.4728)	-1.0622 (0.6476)	0.0731 (0.5790)	-0.1511 (0.5347)	-1.7508** (0.7159)
INDEX	0.0961 (0.4484)	-0.0508 (0.4396)	-0.2766 (0.4629)	-0.1336 (0.1141)	-0.0619 (0.1043)	-0.0957 (0.1100)
INDEX^2	0.0092 (0.0743)	0.0091 (0.0725)	0.0340 (0.0744)	0.0089 (0.0101)	0.0043 (0.0093)	0.0106 (0.0097)
ISLAND	-0.2103* (0.1212)	-0.2517** (0.1185)	-0.1631 (0.1407)	-0.2244 (0.1432)	-0.2831** (0.1329)	-0.2354 (0.1634)
Lag ERROR	0.0934 (0.0709)			0.1270 (0.0810)		
Spatial Lag		0.1680** (0.0657)	0.1361** (0.0669)		0.2109** (0.0895)	0.2401** (0.0935)
Lag – PEVP			0.1282* (0.0754)			0.0733 (0.0913)
Lag - POPD			-0.7625 (0.5173)			-0.5382 (0.5759)
Lag - GCPOP			0.0578 (0.0896)			0.1835* (0.1051)
Lag –INDEX			0.0455 (0.0724)			-0.1162 (0.0880)
N	102	102	102	98	98	98
R^2	0.3425	0.3451	0.3828	0.3744	0.3752	0.4090

***, **, * - - statistical significant at the 0.01, 0.05, and 0.10 levels, respectively.

Figures in the parentheses are standard errors.

In accordance with earlier findings (Pandit and Laband 2007a, 2007b), it is found that imperilment of vascular plants, but no other taxa groups, is influenced significantly by human population density. Also in accord with findings in earlier chapters, concentration in the human population seems to be positively related to imperilment of birds, mammals, and perhaps reptiles and negatively related to imperilment of amphibians and vascular plants. There is some evidence that species imperilment is lower among island-based birds, amphibians, and vascular plants than among continent-based species in those taxa; this counter-intuitive finding may be an artifact of the timing of this cross-sectional analysis. The observation that island-based mammals are more imperiled than continent-based mammals is consistent with the expectations.

There is a significant relationship between the percentage of imperiled birds, mammals, and reptiles and the Economic Freedom Index. Structurally, this relationship resembles the EKC, with species imperilment increasing as EFI increases at a decreasing rate. Since EFI is scaled such that lower values are associated with greater economic freedom, this means that as economic freedom declines, species imperilment increases, albeit at a decreasing rate. Depending on taxa group and model specification, the saddle point falls in the range of 2.9 – 3.15. From this point along the EFI continuum (1 – 5), species imperilment among birds, mammals, and reptiles declines as a country moves in either direction. This finding, then, is consistent with the relatively high degree of correlation between economic freedom and measures of economic performance, such as per capita GDP. However, no evidence of a statistically significant relationship is found between EFI and imperilment of either amphibians or vascular plants.

There is much less consistent/compelling evidence of a relationship between corruption and species imperilment. The estimated effect of corruption is statistically insignificant across all taxa except birds. Among birds, the relationship is a quadratic: The percent of imperiled birds rises as CPI rises, at a decreasing rate. Depending on model specification, the turning point is a CPI in the range of 5.25 – 5.50. This is very close to the threshold identified by Transparency International that defines corrupt regimes (below 5.0) from non-corrupt regimes (above 5.0). Thus, above this threshold, decreasing corruption is associated with decreasing species imperilment among birds. However, it is emphasized that this is the only taxa for which a significant relationship is found. This puts the analysis a bit at odds with previous studies (Lopez and Mitra 2000; Damania, Fredriksson, and List 2003) that looked at the effect of corruption on environmental quality. These studies identified a negative relationship between corruption and environmental protection.

Finally, the variables that control for general spatial dependency are uniformly significant across taxa groups, in both the EFI and CPI models. Also in both sets of models, fairly consistent evidence across taxa groups is found that the species imperilment in a country is related negatively to the percent of endemic species in neighboring countries. There are indications of other specific cross-border effects that are significant, but these are sensitive to the taxa group under consideration.

5.5 Concluding Remarks

So far as the empirical work is concerned, this is the first to consider the impact of economic freedom and corruption on species imperilment, controlling explicitly for cross-border effects. In their pathbreaking work in this area, McPherson and

Nieswiadomy (2005) included measures of legal institutions, civil liberties, and political

unrest in their cross-country analysis of species fragility, but their focus was on the

Environmental Kuznets Curve relationship, so they also included measures of economic

performance as explanatory variables. However, the focus here is on economic freedom

rather than civil/political liberty. Because economic freedom and corruption indices are

highly correlated with measures of economic performance, one cannot generate reliable

estimates of the impact of either on species imperilment if both are included in the model.

Moreover, since an analysis that aggregates species across taxa will be dominated by the

vascular plants, an aggregate analysis may not reveal important taxa-level impacts.

Therefore, the empirical analysis focuses on 5 taxa: birds, mammals, reptiles,

amphibians, and vascular plants. Based on data from 152 countries, the empirical

analysis suggests that there are statistically significant relationships between imperilment

of birds, mammals, and reptiles and economic freedom. However, the evidence of a

statistically significant relationship between corruption and species imperilment is found

only among birds.

CHAPTER 6

CONCLUSION

This dissertation research focuses on two aspects of species imperilment, using

country-level data for five taxa. First is an empirical issue dealing with the impacts of

spatial concentration of humans, economic freedom, and corruptions on species

imperilment. Second is a methodological issue related to spatial autocorrelation, its

measures, and the general and specific aspects of its controls on empirical models of

species imperilment.

Public policies that encourage high-density human living arrangements have been

predicated explicitly on the assumption that certain spatial distributions of a fixed-size

human population are more environmentally friendly than others. Empirical analysis of

the assumption that the spatial concentration of human presence in each country is related

statistically to the percentage of imperiled species reveals that spatial concentration of the

human population is associated with reduced imperilment among amphibians and

vascular plants but increased imperilment among mammals, reptiles, and birds. The

findings for some taxa, but not for all, are consistent with the assumed positive impacts of

concentrating humans for other species conservation through smart-growth principles of

compact building design. Similarly, empirical analysis of conjectured link between

economic freedom and corruption and species imperilment has shown that there are

statistically significant relationships between imperilment of birds, mammals, and reptiles

and economic freedom. However, the relationship between corruption and species

imperilment is found to be significant only among birds. The results suggest that beyond

certain thresholds, more economic freedom is associated with reduced species

imperilment in a country.

Regarding the methodological issue, the species imperilment data for all species

taxa are plagued by spatial autocorrelation in all modes of spatial adjacency measures.

The presence of spatial autocorrelation suggests that the factors that influence species

imperilment extend beyond arbitrary political boundaries. It further suggests that a check

and control for spatial autocorrelation is necessary to correct the impact of a dependency-

related omitted variable problem in spatial data when individual countries are the unit of

analysis.

A simple adjacency measure of the spatial dependency out-performed the other

three measures of spatial dependency: 2nd order, centroid distance, and percent shared

border length adjacency measures. The simple adjacency measure was based on a simple

dummy nature of adjacency as compared to more sophisticated adjacency matrices for

other measures. The result suggests that a simple specification of adjacency is sufficient

for empirical research that seeks to control for spatial autocorrelation, at least in the

context of estimating the determinants of species imperilment at a country-level of

analysis. Among alternative specifications of the spatial model, spatial error models

explain more variation than spatial lag models for all taxa except for reptiles. However,

the spatial error models are less intuitive than lag models on interpretation of the lagged

error term.

The general correction for spatial autocorrelation in the form of spatial lag or error lag only corrects the omitted variable problem in the models but adds little to nothing to our understanding of the spatial linkage between other model variables. The use of both general and specific controls for spatial autocorrelation in the model helps to describe the spatial relationships of independent variables as well. The results indicate that the addition of spatial controls based on specific cross-border effects can substantially change the size and statistical significance of the general spatial dependency term as well as the size, sign, and/or statistical significance of the explanatory variables. The use of both general and specific spatial controls helps to elucidate spatial relationship in a finer scale. Using specific variable lags one can infer the cross-border impacts of the variable of interest as opposed to either one of the general spatial controls, a summative spatial lag or unintuitive error lag.

The results highlighted above will be useful for empirical research involving geographic data which have inherent limitations posed by arbitrary political boundaries. More importantly, the findings of this research open an avenue for a policy dialogue and finer scale research in order to shape species conservation policies across and within countries, when conjecturing the widely held beliefs and empirical evidence about the impacts of spatial distribution of humans, economic freedom, and corruption on species imperilment.

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APPENDICES

APPENDIX-I Map of Sample Countries by Taxa

Sample Countries for Birds, Mammals, and Reptiles

Legend

☐ Countries

0   30   60   120 Decimal Degrees

Sample Countries for Amphibians

Legend

☐ Countries

0   30   60   120 Decimal Degrees
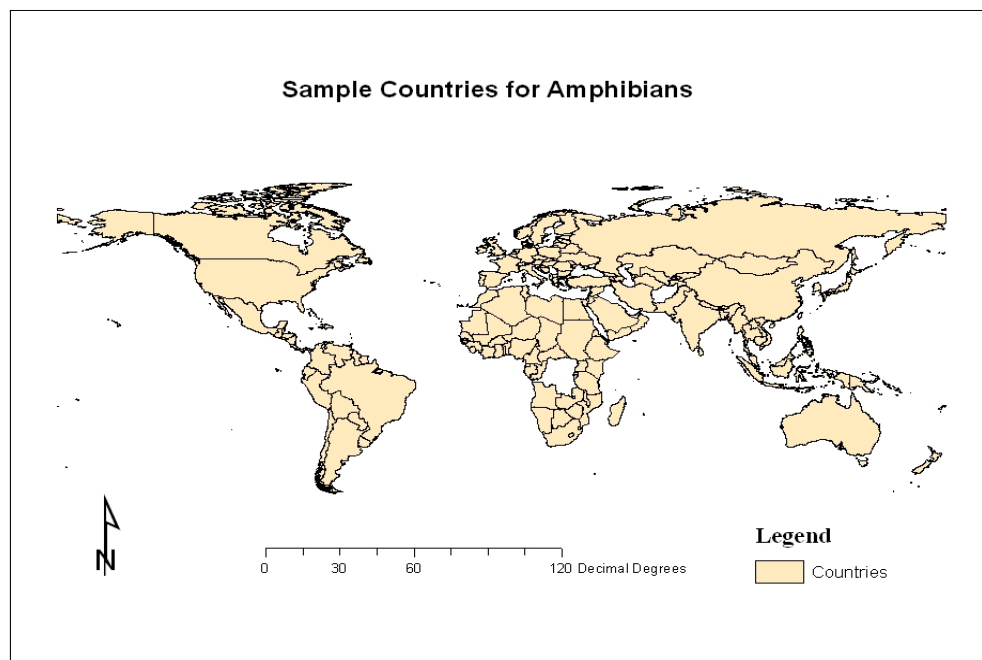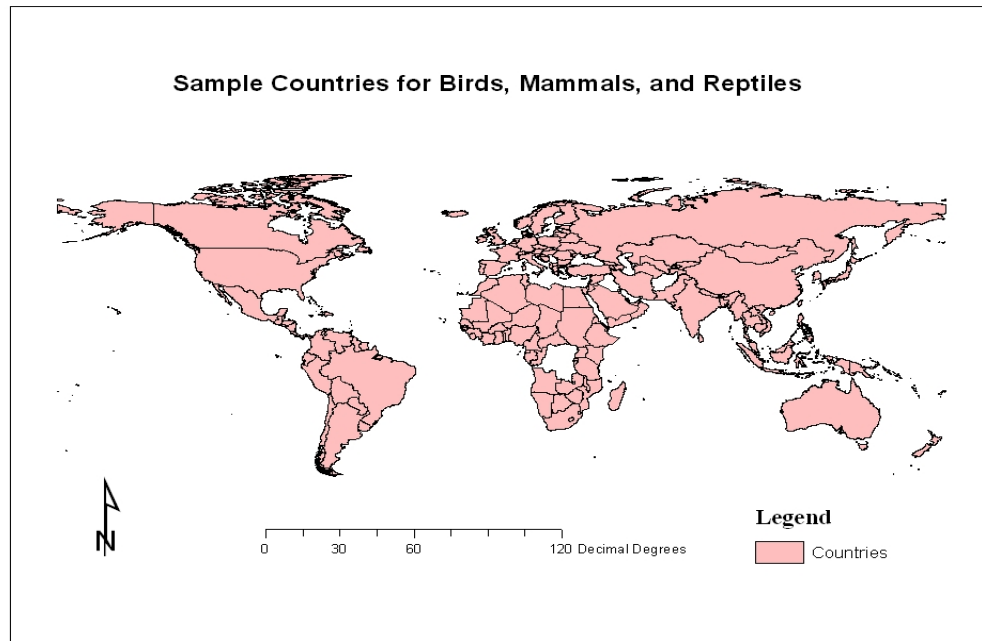
Sample Countries for Vascular Plants
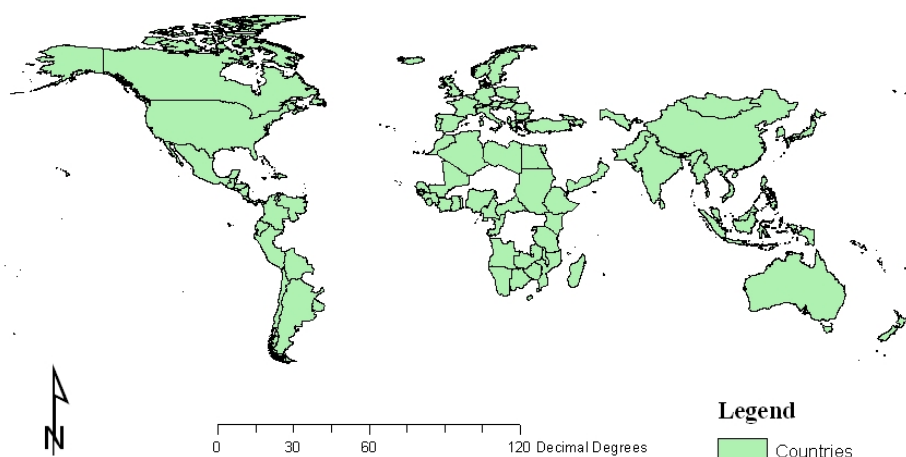
APPENDIX-II Cluster and Significance Maps for Mammals, Reptiles, Amphibians, and

Vascular Plants

Appendix-II.1 Cluster Map for the Nature of Spatial Autocorrelation Among Imperiled
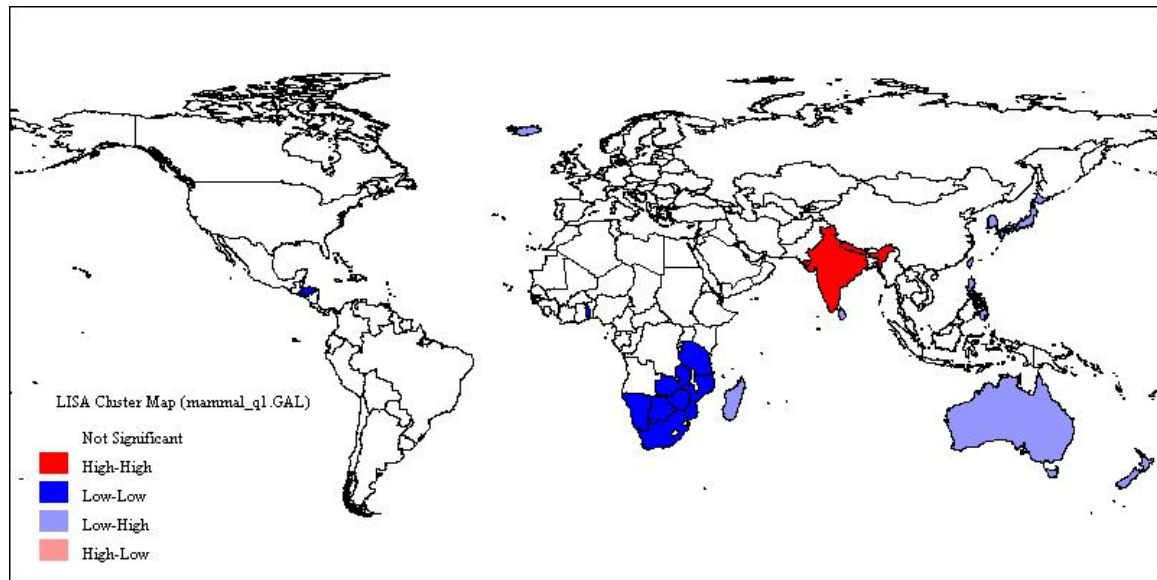
Mammals

Appendix-II.2 Significance Map for the Intensity of Spatial Autocorrelation Among

Imperiled Mammals
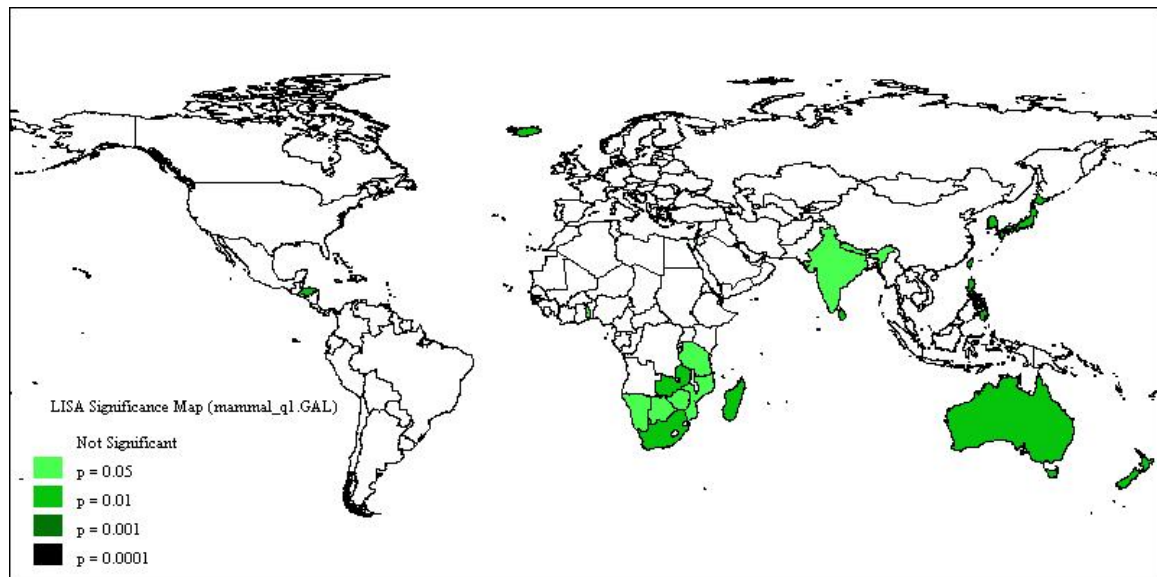
Appendix-II.3 Cluster Map for the Nature of Spatial Autocorrelation Among Imperiled
Reptiles
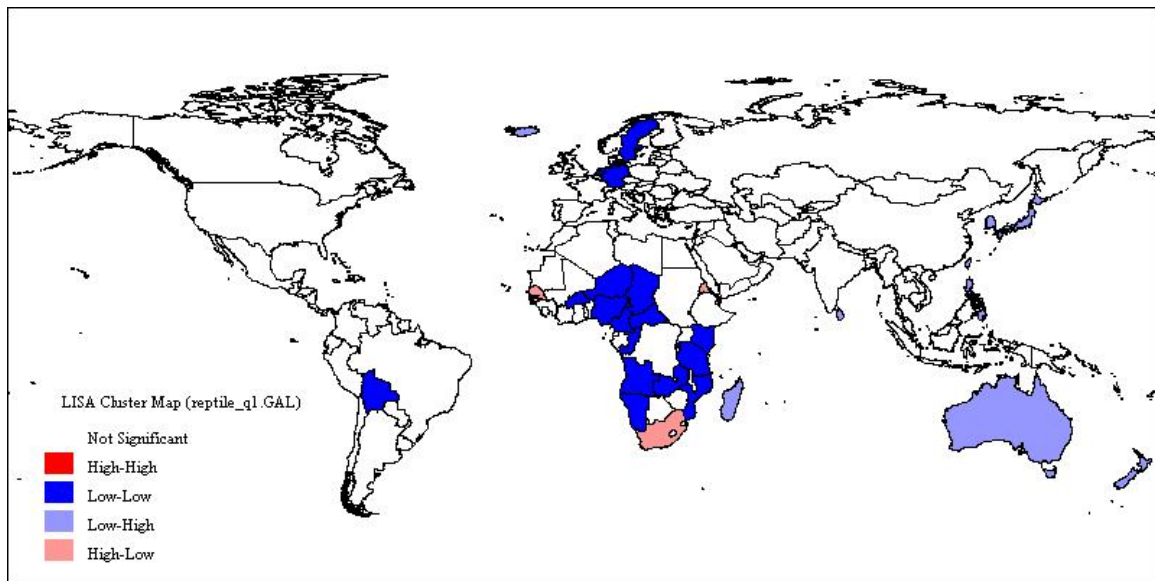
Appendix-II.4 Significance Map for the Intensity of Spatial Autocorrelation Among

Imperiled Reptiles
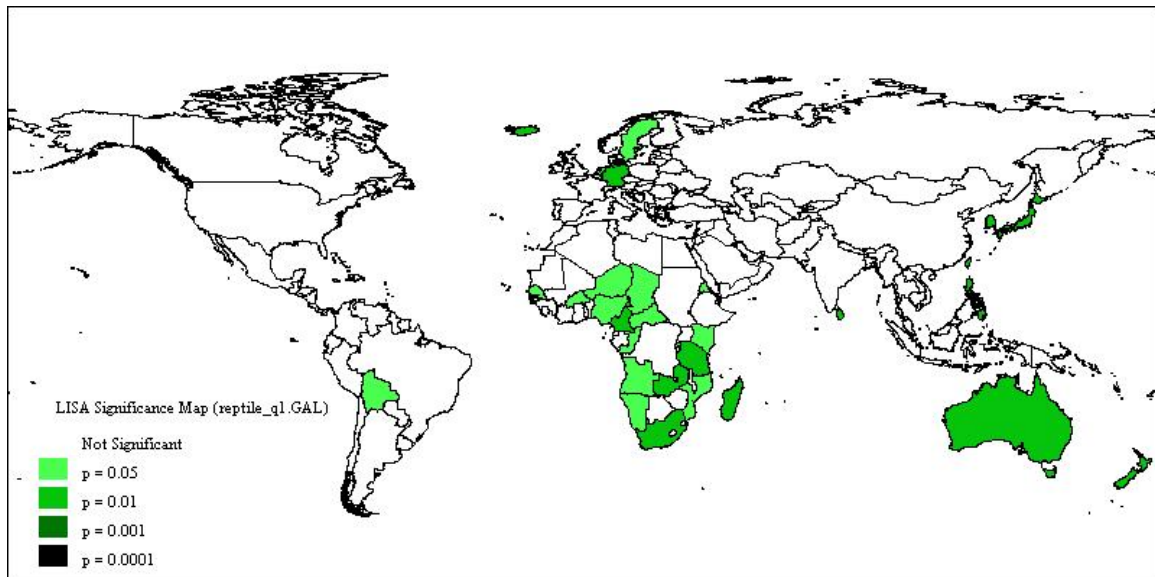
Appendix-II.5 Cluster Map for the Nature of Spatial Autocorrelation Among Imperiled
Amphibians
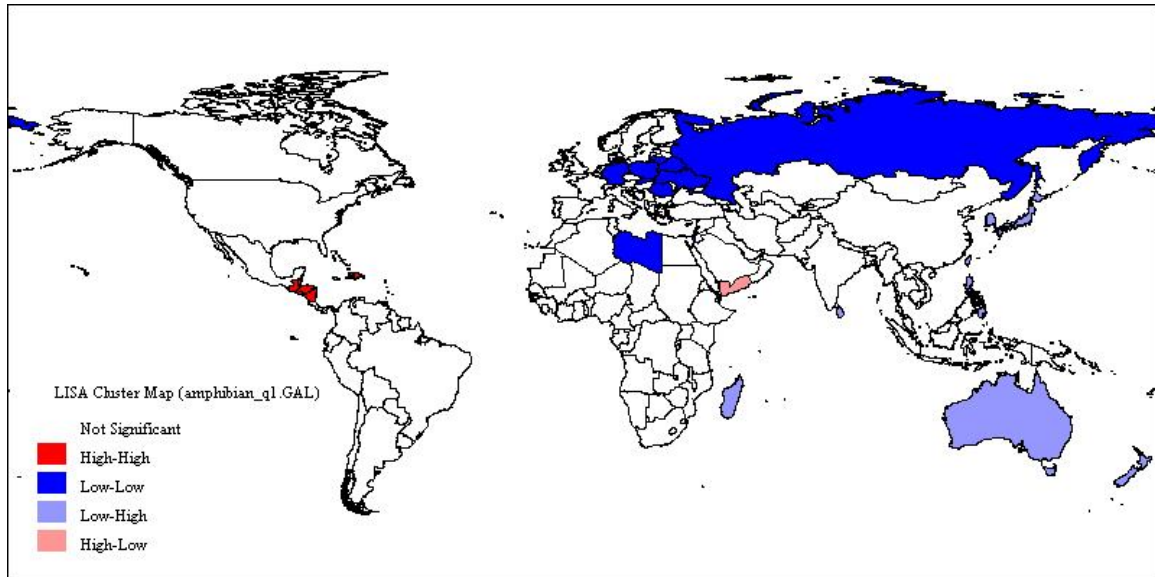
Appendix-II.6 Significance Map for the Intensity of Spatial Autocorrelation Among
Imperiled Amphibians
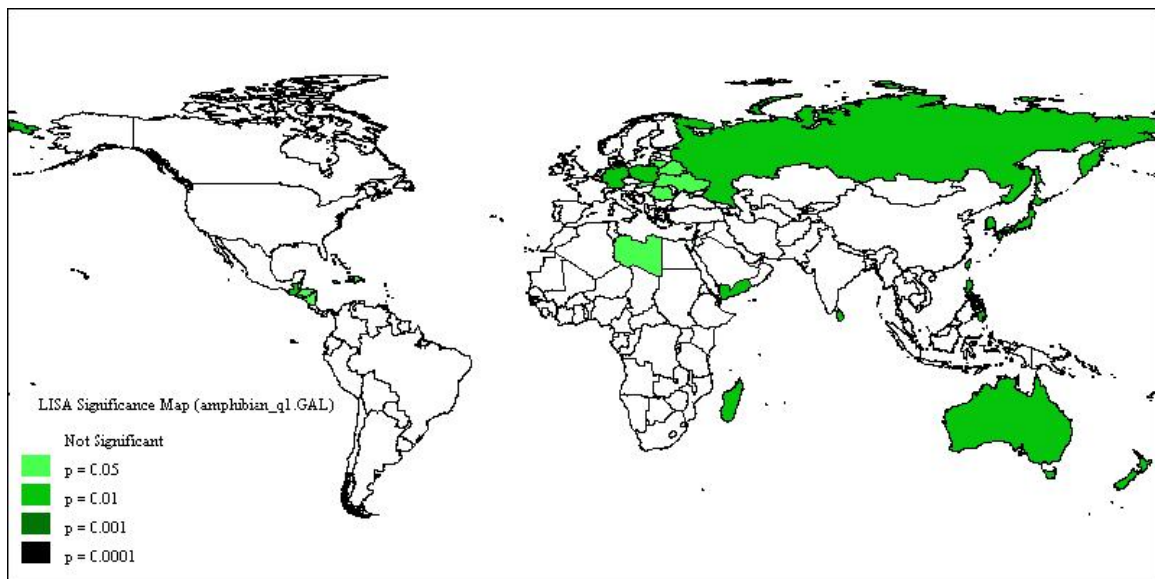
Appendix-II.7 Cluster Map for the Nature of Spatial Autocorrelation Among Imperiled
Vascular Plants
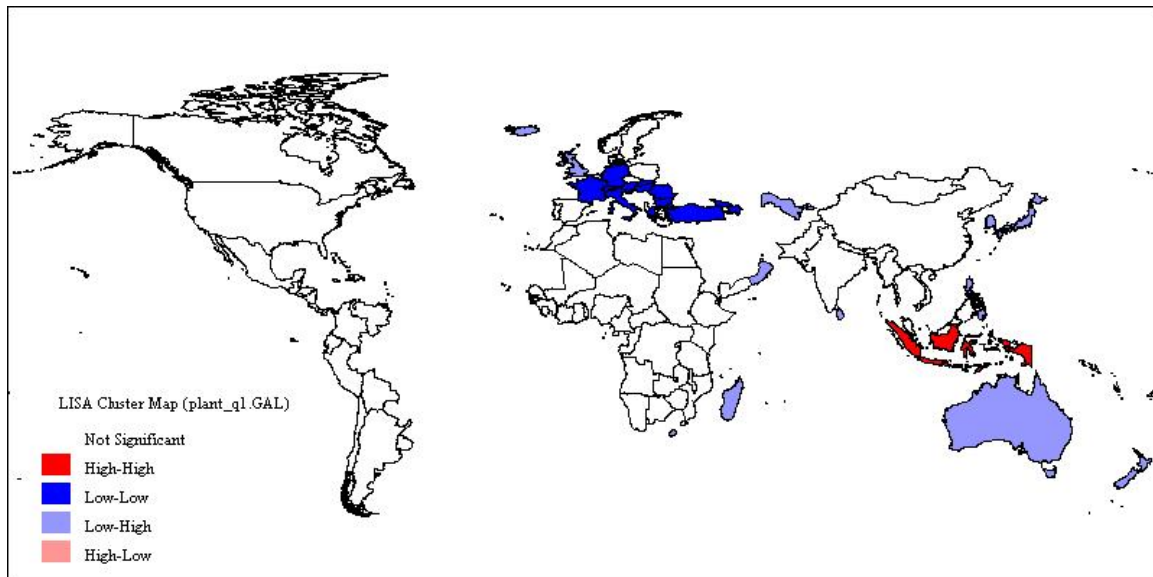
Appendix-II.8 Significance Map for the Intensity of Spatial Autocorrelation Among
Imperiled Vascular Plants
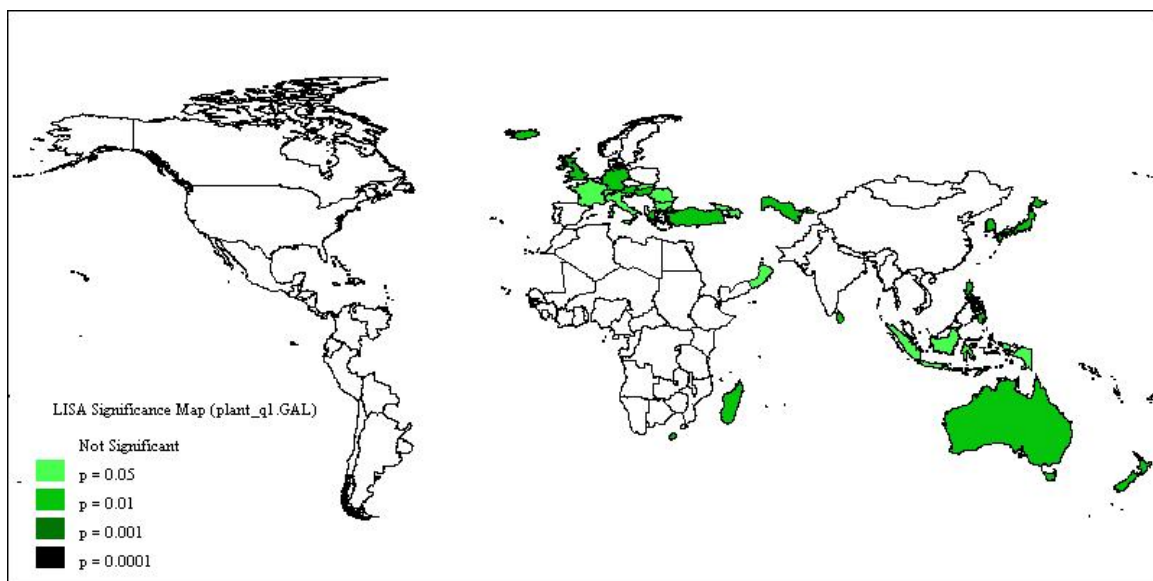
APPENDIX-III Other Adjacency Measures Based Weighted Least Squares Regression

Results for Factors Influencing Species Imperilment

Table III.1: Spatial Lag Models: 2nd Order Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.9137**	8.4019***	3.639	20.3056***	0.4232
	(0.8477)	(2.7575)	(2.2489)	(5.6596)	(0.3958)
PES	0.3415***	0.3206***	0.0086	0.4827***	0.0100***
	(0.0173)	(0.0337)	(0.0155)	(0.0313)	(0.0023)
POPD	0.4547	5.7587***	-0.2652	-1.7299*	0.3187***
	(0.4923)	(2.1716)	(0.4115)	(1.0342)	(0.0573)
GCPOP	0.7019	-0.9274	0.8653	-19.8343***	0.0079
	(0.9526)	(3.1937)	(2.5744)	(6.5454)	(0.4739)
PCGDDP	0.0422**	0.1496	0.0257	0.2509*	-0.0325**
	(0.0191)	(0.0976)	(0.0539)	(0.1398)	(0.0136)
PCGDP^2	-0.0010**	-0.0051*	-0.0009	-0.0056*	0.0008*
	(0.0005)	(0.0029)	(0.0013)	(0.0033)	(0.0004)
ISLAND	-1.3091***	0.8247	0.77	-1.7503	-0.0036
	(0.2482)	(0.8293)	(0.6896)	(1.7582)	(0.0899)
LAG PIS	1.8663***	4.8485***	5.0099***	5.8307***	0.1511*
	(0.2111)	(0.7391)	(0.7346)	(1.5609)	(0.0836)
N	173	173	173	163	117
R^2	0.7277	0.5713	0.45	0.5308	0.3162
% Δ in R^2 From Model 1 (Table 4.4)	+21.8	+60.9	+83.9	+3.1	+23.3

Table III.2: Spatial Error Models: 2nd Order Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.5835**	6.1941**	0.9299	18.1384***	0.3507
	(0.7601)	(2.6237)	(2.3312)	(5.2727)	(0.3919)
PES	0.5126***	0.3291***	0.0029	0.5007***	0.0102***
	(0.0203)	(0.0349)	(0.0168)	(0.0289)	(0.0023)
POPD	-0.0577	-0.8532*	-0.2298	-1.3258	0.3261***
	(0.1558)	(0.5073)	(0.4472)	(0.9891)	(0.0572)
GCPOP	0.1239	2.2038	2.6942	-17.1118***	0.0883
	(0.902)	(3.0906)	(2.7489)	(6.177)	(0.4708)
PCGDDP	0.0902***	-0.0252	0.0059	0.1120	-0.0351**
	(0.0307)	(0.0669)	(0.0582)	(0.1349)	(0.0136)
$PCGDP^2$	-0.0023**	-0.0010	-0.0008	-0.0037	0.0008**
	(0.0009)	(0.0016)	(0.0014)	(0.0031)	(0.0004)
ISLAND	-1.1601***	3.4582***	3.1105***	-1.1049	0.0256
	(0.2545)	(0.786)	(0.7322)	(1.6835)	(0.0891)
LAG ERROR	1.6363***	4.9906***	3.6221***	9.2704***	0.1298*
	(0.1732)	(0.6646)	(0.631)	(1.6451)	(0.0732)
N	173	173	173	163	117
R^2	0.7471	0.5951	0.3773	0.5733	0.3347
% Δ in R^2 From Model 1 (Table 4.4)	+25.1	+67.6	+54.2	+11.3	+30.5

Table III.3: Spatial Lag Models: Centroid Distance Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.3027	7.6572***	-0.2460	19.8946***	0.2847
	(0.8226)	(2.9295)	(2.5072)	(5.9282)	(0.3976)
PES	0.4179***	0.3062***	0.0108	0.4431***	0.0096***
	(0.0237)	(0.0384)	(0.0175)	(0.0333)	(0.0025)
POPD	0.9902*	-1.2755**	-0.0527	-1.5571	0.3121***
	(0.5357)	(0.5675)	(0.4661)	(1.0517)	(0.0594)
GCPOP	1.8489*	0.7031	3.6272	-19.1575***	0.1285
	(0.9549)	(3.4784)	(2.9812)	(6.8005)	(0.477)
PCGDDP	0.1351***	0.1351	0.0884	0.175	-0.0289**
	(0.0319)	(0.111)	(0.0913)	(0.1425)	(0.0144)
PCGDP^2	-0.0036***	-0.0049	-0.0032	-0.0055*	0.0007*
	(0.0009)	(0.0033)	(0.0027)	(0.0033)	(0.0004)
ISLAND	-1.2671***	1.5359*	1.4566*	-0.6801	0.0125
	(0.2868)	(0.8453)	(0.7876)	(1.819)	(0.0905)
LAG PIS	1.8342***	5.1200***	1.4663**	4.7824**	0.1514
	(0.2152)	(0.781)	(0.6413)	2.2381)	(0.1605)
N	173	173	173	163	117
R^2	0.6619	0.4629	0.2906	0.5209	0.2982
% Δ in R^2 From Model 1 (Table 4.4)	+10.8	+30.4	+18.8	+1.2	+16.3

Table III.4: Spatial Error Models: Centroid Distance Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.5499	1.3956	-0.1318	17.3670***	0.4526
	(0.7341)	(2.6538)	(2.6205)	(5.754)	(0.4021)
PES	0.4026***	0.3220***	0.0108	0.4604***	0.0103***
	(0.0216)	(0.0378)	(0.0178)	(0.0317)	(0.0023)
POPD	0.4825	-1.1221**	-0.1062	-1.3324	0.3314***
	(0.4853)	(0.5628)	(0.4824)	(1.0572)	(0.0576)
GCPOP	1.4114	8.3713***	3.5701	-16.8607**	-0.0192
	(0.8585)	(3.1318)	(3.1279)	(6.6985)	(0.4793)
PCGDDP	0.124***	-0.0632	0.0677	0.1463	-0.0338**
	(0.0287)	(0.073)	(0.0929)	(0.1437)	(0.0136)
PCGDP^2	-0.0034***	-0.0000	-0.0030	-0.0052	0.0007*
	(0.0008)	(0.0017)	(0.0027)	(0.0034)	(0.0004)
ISLAND	-0.8178***	2.3362***	1.8183**	0.0834	-0.0329
	(0.2584)	(0.8183)	(0.7724)	(1.7916)	(0.0951)
LAG ERROR	2.1992***	5.1971***	1.9781**	4.6056	-0.2599
	(0.1857)	(0.7221)	(0.8643)	(3.175)	(0.1624)
N	173	173	173	163	117
R^2	0.7171	0.542	0.3052	0.517	0.296
% Δ in R^2 From Model 1 (Table 4.4)	+20.0	+52.6	+24.7	+0.4	+15.4

Table III.5: Spatial Lag Models: Shared Border Length Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-0.2216	1.865	-2.6323	16.0075***	0.4724
	(0.6791)	2.6002)	(2.1547)	(5.8025)	(0.3753)
PES	0.3486***	0.3247***	0.0152	0.4217***	0.0085***
	(0.0174)	(0.0349)	(0.0162)	(0.0306)	(0.0022)
POPD	0.0626	-1.0157**	-0.0305	-1.7213	-0.2026
	(0.141)	(0.5054)	(0.427)	(1.1273)	(0.25)
GCPOP	0.7521	-1.8118	3.6642	-19.2987***	-0.4395
	(0.8455)	(3.1173)	(2.6018)	(6.855)	(0.4386)
PCGDDP	0.0951***	0.0714	0.0225	0.2457*	0.0085
	(0.0281)	(0.0667)	(0.0568)	(0.152)	(0.0134)
PCGDP^2	-0.0027***	-0.0022	-0.0010	-0.0062*	-0.0004
	(0.0008)	(0.0016)	(0.0013)	(0.0035)	(0.0004)
ISLAND	0.2990	9.6495***	4.5883***	2.6658	0.2587***
	(0.3027)	(1.1688)	(0.7732)	(1.9787)	(0.0968)
LAG PIS	0.4928***	0.7894***	0.7282***	0.3870***	0.2865***
	(0.0532)	(0.0921)	(0.1061)	(0.0637)	(0.0423)
R^2	0.7603	0.562	0.4376	0.5429	0.3524
N	173	173	173	163	117
% Δ in R^2 From Model 1 (Table 4.4)	+27.3	+58.3	+78.8	+5.4	+37.4

Table III.6: Spatial Error Models: Shared Border Length Adjacency

Variables	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.6445	0.2863	1.1588	17.7281***	0.2983
	(0.6383)	(2.4207)	(2.0221)	(5.0737)	(0.3908)
PES	0.4370***	0.3529***	0.003	0.4895***	0.0105***
	(0.0236)	(0.0355)	(0.0151)	(0.0293)	(0.0023)
POPD	0.0078	-0.7196	-0.139	-1.2699	0.3322***
	(0.1322)	(0.5176)	(0.3929)	(0.9758)	(0.0573)
GCPOP	1.1206	5.8652**	1.9792	-16.0795***	0.1643
	(0.7639)	(2.9203)	(2.4219)	(5.9853)	(0.4706)
PCGDP	0.1077***	-0.0369	0.1328*	0.0768	-0.0362***
	(0.0268)	(0.0679)	(0.0808)	(0.1332)	(0.0137)
$PCGDP^2$	-0.0028***	-0.0008	-0.006*	-0.0032	-0.0008*
	(0.0008)	(0.0016)	(0.0025)	(0.0031)	(0.0004)
ISLAND	-1.0891***	2.6265***	2.0347***	-1.0554	0.0118
	(0.2335)	(0.7833)	(0.6489)	(1.6711)	(0.089)
LAG ERROR	0.8361***	0.893***	0.7106***	0.4482***	0.059*
	(0.0723)	(0.0971)	(0.097)	(0.0681)	(0.0316)
N	173	173	173	163	117
R^2	0.7958	0.6535	0.4208	0.5683	0.3311
% Δ in R^2 From Model 1 (Table 4.4)	+33.2	+84.0	+72.0	+10.4	+29.1

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Figures in the parentheses are standard errors.

APPENDIX-IV Other Adjacency Based Weighted Least Squares Regression Results for

General and Specific Spatial Lags on Species Imperilment

Model IV.1: Models with General Spatial Lag: 2nd Order Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.9137**	8.4019***	6.3690	20.3056***	0.4232
	(0.8477)	(2.7575)	(2.2489)	(5.6596)	(0.3958)
PES	0.3415***	0.3206***	0.0086	0.4823***	0.0100***
	(0.0173)	(0.0337)	(0.0155)	(0.0313)	(0.0023)
POPD	0.4547	5.7578***	-0.2652	-1.7299*	0.3185***
	(0.4923)	(2.1716)	(0.4115)	(1.0342)	(0.0573)
GCPOP	0.7019	-0.9274	0.8653	-19.8343***	0.0079
	(0.9526)	(3.1937)	(2.5744)	(6.5454)	(0.4739)
PCGDP	0.0422**	0.1496	0.0257	0.2509*	-0.0325**
	(0.0191)	(0.0976)	(0.0539)	(0.1398)	(0.0136)
PCGDP^2	-0.0010**	-0.0051*	-0.0009	-0.0056**	0.0008*
	(0.0005)	(0.0029)	(0.0013)	(0.0033)	(0.0004)
ISLAND	-1.3091***	0.8247	0.7700	-1.7503	-0.0036
	(0.2482)	(0.8293)	(0.6896)	(1.7582)	(0.0899)
SL – General	1.8663***	4.8485***	5.0099***	5.8307***	0.1511*
	(0.2111)	(0.7391)	(0.7346)	(1.5609)	(0.0836)
N	173	173	173	163	117
R^2	0.7277	0.5713	0.4500	0.5308	0.3162

Model IV.2: Models with General and Specific Spatial Lags: 2nd Order Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.9281	7.1962	3.5300	16.2713***	0.8947*
	(0.8118)	(3.4959)	(2.6554)	(5.8123)	(0.4665)
PES	0.5345***	0.2869***	0.0074	0.5168***	0.0094***
	(0.0188)	(0.0335)	(0.0160)	(0.0261)	(0.0024)
POPD	0.0007	-0.6127	-0.3515	-1.3428	0.2783***
	(0.1431)	(0.5558)	(0.4279)	(0.8866)	(0.0603)
GCPOP	0.3555	3.5440	0.5143	-18.1970***	-0.6608
	(0.9557)	(4.1088)	(3.1344)	(6.6859)	(0.5612)
PCGDP	0.0651**	-0.0832	0.0679	0.0808	-0.0255*
	(0.0305)	(0.0801)	(0.0623)	(0.1371)	(0.0148)
PCGDP^2	-0.0017**	-0.0007	-0.0013	-0.0013	0.0006
	(0.0008)	(0.0017)	(0.0013)	(0.0028)	(0.0004)
ISLAND	-0.6869**	1.4507	0.8857	1.5366	0.0732
	(0.3142)	(1.0692)	(0.8365)	(1.7781)	(0.1233)
SL – General	2.4131***	5.3795***	4.9507***	18.9995***	0.0775
	(0.3139)	(0.9466)	(0.9999)	(1.1504)	(0.0933
SL – PES	-4.3031***	-1.1711	-0.1969	-11.4818***	-0.1209
	(0.4795)	(0.8902)	(0.6369)	(1.5916)	(0.1310)
SL – POPD	1.8826	4.2714	0.2594	-20.1433***	-0.1783
	(1.1831)	(4.2298)	(3.6485)	(6.85556)	(0.5580)
SL – GCPOP	0.0701	-0.6061	0.1075	1.1883	0.2587**
	(0.2135)	(0.7476)	(0.6020)	(1.1282)	(0.1134)
SL – PCGDP	-0.2120	1.0740*	-0.6893	0.6874	-0.1026
	(0.1650)	(0.6156)	(0.4953)	(1.0490)	(0.0868)
N	173	173	173	163	117
R^2	0.7613	0.6221	0.4946	0.6218	0.3686

Model IV.3: Models with Specific Spatial Lags only: 2nd Order Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.3153	3.5782	1.6826	16.5001**	0.8137*
	(1.1379)	(4.0851)	(2.8863)	(7.0754)	(0.4465)
PES	0.3883***	0.3161***	0.0020	0.4632***	0.0088***
	(0.0249)	(0.0398)	(0.0177)	(0.0316)	(0.0023)
POPD	0.7528	-2.4664	-0.2026	-1.4161	0.2761***
	(0.6207)	(2.4237)	(0.4685)	(1.0726)	(0.0576)
GCPOP	1.5138	8.2058*	2.6512	-15.3120*	-0.6004
	(1.2965)	(4.7112)	(3.4271)	(8.1796)	(0.5368)
PCGDP	0.0825**	-0.0689	0.1783*	0.1264	-0.0244*
	(0.0379)	(0.1351)	(0.0970)	(0.1644)	(0.0140)
PCGDP^2	-0.0023**	-0.0013	-0.0061**	-0.0048	0.0006*
	(0.0010)	(0.0038)	(0.0028)	(0.0033)	(0.0004)
ISLAND	-1.7671***	-0.0202	1.1527	-0.1407	0.1048
	(0.3737)	(1.2753)	(0.9147)	(2.0726)	(0.1136)
SL – General	-	-	-	-	-
SL – PES	0.2451	-0.6185	-0.3373	0.9869	-0.2004
	(0.4611)	(1.0431)	(0.6971)	(1.4529)	(0.1255)
SL – POPD	4.7848***	13.4178***	11.6686**	3.9715	-0.0708
	(1.3476)	(4.694)	(3.1501)	(8.0039)	(0.5280)
SL – GCPOP	0.5692**	0.2625	1.1265*	-0.6466	0.2772***
	(0.2300)	(0.8300)	(0.6063)	(1.3886)	(0.1043)
SL – PCGDP	-0.0969	0.7959	-1.0471*	0.3679	-0.1399
	(0.2064)	(0.7316)	(0.5352)	(1.2552)	(0.0772)
N	173	173	173	163	117
R^2	0.6945	0.4668	0.4305	0.5239	0.3590

Model IV.4: Models with General Spatial Lag: Centroid Distance Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	0.3027	7.6572***	-0.2460	19.8946***	0.2847
	(0.8226)	(2.9295)	(2.5072)	(5.9282)	(0.3976)
PES	0.4179***	0.3062***	0.0108	0.4431***	0.0096***
	(0.0237)	(0.0384)	(0.0175)	(0.0333)	(0.0025)
POPD	0.9902*	-1.2755**	-0.0527	-1.5571	0.3121***
	(0.5357)	(0.5675)	(0.4661)	(1.0517)	(0.0594)
GCPOP	1.8489*	0.7031	3.6272	-19.1575***	0.1285
	(0.9549)	(3.4784)	(2.9812)	(6.8005)	(0.4770)
PCGDP	0.1351***	0.1351	0.0884	0.1750	-0.0289**
	(0.0319)	(0.1110)	(0.0913)	(0.1425)	(0.0144)
$PCGDP^2$	-0.0036***	-0.0049	-0.0032	-0.0055*	0.0007*
	(0.0009)	(0.0033)	(0.0027)	(0.0033)	(0.0004)
ISLAND	-1.2671***	1.5359*	1.4566*	-0.6801	0.0125
	(0.2868)	(0.8453)	(0.7876)	(1.8190)	(0.0905)
SL – General	1.8342***	5.1200***	1.4663**	4.7824**	0.1514
	(0.2152)	(0.7810)	(0.6413)	(2.2381)	(0.1605)
N	173	173	173	163	117
R^2	0.6619	0.4629	0.2906	0.5209	0.2982

Model IV.5: Models with General and Specific Spatial Lags: Centroid Distance Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	1.0163	6.4177**	0.2130	25.0425***	0.7008*
	(0.8348)	(2.9577)	(2.8233)	(6.1562)	(0.4223)
PES	0.3091***	0.3816***	0.0052	0.4187***	0.0056**
	(0.0160)	(0.0394)	(0.0200)	(0.0326)	(0.0025)
POPD	0.3517	-0.9766*	-0.2683	-2.2641*	0.2514***
	(0.5212)	(0.5314)	(0.5056)	(1.1605)	(0.0591)
GCPOP	1.0801	3.0980	2.6713	-19.4215***	-0.3558
	(0.9638)	(3.4654)	(3.3307)	(7.0327)	(0.4984)
PCGDP	0.1227***	-0.0876	0.1694*	0.1259	-0.0089
	(0.0297)	(0.1037)	(0.1026)	(0.1470)	(0.0140)
$PCGDP^2$	-0.0031***	-0.0011	-0.0067**	-0.0036	0.0003
	(0.0009)	(0.0031)	(0.0031)	(0.0034)	(0.0004)
ISLAND	-0.6023**	2.3495***	3.3172***	-3.0886	-0.0626
	(0.2683)	(0.7913)	(0.8754)	(2.0348)	(0.0943)
SL – General	5.0834***	6.1320***	1.3725*	-34.7465***	-0.2178
	(0.4225)	(1.0142)	(0.8376)	(9.2482)	(0.2088)
SL – PES	-3.5383***	-3.4760***	-1.3886*	50.8479***	0.3691***
	(0.3837)	(0.9185)	(0.7799)	(11.9813)	(0.1097)
SL – POPD	-1.7295***	2.3242	2.1435*	-45.0926***	0.7232***
	(0.4102)	(1.4243)	(1.1721)	(9.2874)	(0.1441)
SL – GCPOP	-0.5477**	-0.3612	0.9739	6.5247	-0.0591
	(0.2560)	(0.9145)	(0.9907)	(7.1772)	(0.1134)
SL – PCGDP	-0.6305***	0.3966***	-1.1356	15.7145**	-0.1001
	(0.2139)	(0.7681)	(0.9338)	(6.1557)	(0.1015)
N	173	173	173	163	117
R^2	0.7356	0.6149	0.3690	0.5554	0.4254

Model IV.6: Models with Specific Spatial Lags only: Centroid Distance Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-0.1590	5.2253*	-4.4018	25.0670***	0.6703
	(0.9609)	(3.0177)	(2.7276)	(6.1111)	(0.4215)
PES	0.2996***	0.3462***	-0.0334*	0.4661***	0.0053**
	(0.0178)	(0.0360)	(0.0186)	(0.0330)	(0.0024)
POPD	1.0111*	-0.4084	12.4238***	-0.8875	0.2462***
	(0.5949)	(0.5327)	(1.8724)	(1.1119)	(0.0589)
GCPOP	2.4415**	1.6924	6.8799**	-22.5830***	-0.3306
	(1.1223)	(3.5703)	(3.1898)	(6.9569)	(0.4981)
PCGDP	0.1006***	0.1231	0.1941**	0.3109**	-0.0075
	(0.0349)	(0.1130)	(0.0969)	(0.1445)	(0.0139)
$PCGDP^2$	-0.0024**	-0.0042	-0.0071**	-0.0061*	0.0002
	(0.0010)	(0.0034)	(0.0029)	(0.0034)	(0.0004)
ISLAND	-1.4370***	0.9514	3.9253***	-5.6295***	-0.0451
	(0.3095)	(0.8531)	(0.8207)	(1.9989)	(0.0928)
SL – General	-	-	-	-	-
SL – PES	0.3199*	-6.2212***	-0.4861	20.9798***	0.3076***
	(0.1870)	(1.4545)	(0.7188)	(4.4969)	(0.0926)
SL – POPD	1.2024***	10.4849***	1.8266*	-6.4645	0.7083***
	(0.3990)	(1.4815)	(1.0832)	(4.7794)	(0.1435)
SL – GCPOP	0.8334***	0.7074	1.4710*	-8.9916	-0.0294
	(0.2744)	(0.9731)	(0.8868)	(6.9143)	(0.1098)
SL – PCGDP	-0.3739	-0.8474	-2.1458**	23.3639***	-0.0486
	(0.2549)	(1.1629)	(0.8634)	(5.8374)	(0.0888)
N	173	173	173	163	117
R^2	0.6628	0.5543	0.3682	0.5521	0.4105

Model IV.7: Models with General Spatial Lag: Shared Border Length Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-0.2216	1.8650	-2.6323	16.0075***	0.4724
	(0.6791)	(2.6002)	(2.1547)	(5.8025)	(0.3753)
PES	0.3486***	0.3247***	0.0152	0.4217***	0.0085***
	(0.0174)	(0.0349)	(0.0162)	(0.0306)	(0.0022)
POPD	-0.0626	-1.0157**	-0.0305	-1.7213	-0.2026
	(0.1410)	(0.5054)	(0.4270)	(1.1273)	(0.2500)
GCPOP	0.7521	-1.1881	3.6642	-19.2987***	-0.4395
	(0.8455)	(3.1173)	(2.6018)	(6.8550)	(0.4386)
PCGDP	0.0951***	0.0714	0.0225	0.2457*	-0.0085
	(0.0281)	(0.0667)	(0.0568)	(0.1520)	(0.0134)
PCGDP^2	-0.0027***	-0.0022	-0.0010	-0.0062*	-0.0004
	(0.0008)	(0.0016)	(0.0013)	(0.0035)	(0.0004)
ISLAND	0.2990***	9.6495***	4.5883***	2.6658	0.2587***
	(0.3027)	(1.1688)	(0.7783)	(1.9787)	(0.0968)
SL – General	0.4928***	0.7894***	0.7282***	0.3870***	0.2865***
	(0.0532)	(0.0921)	(0.1061)	(0.0637)	(0.0423)
N	173	173	173	163	117
R^2	0.7603	0.5620	0.4376	0.5429	0.3524

Model IV.8:   Models with General and Specific Spatial Lags: Shared Border Length
            Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-0.2951	-0.5921	-1.6719	17.4599**	0.3393
	(1.0925)	(4.0553)	(3.3777)	(7.8713)	(0.4804)
PES	0.4446***	0.3514***	-0.0014	0.4955***	0.0081***
	(0.0227)	(0.0351)	(0.0165)	(0.0303)	(0.0024)
POPD	0.0598	-0.9035*	-0.2976	-1.2936	-0.1595
	(0.1266)	(0.5119)	(0.4274)	(1.0321)	(0.2788)
GCPOP	1.2067	4.1737	6.9034**	-19.3755**	-0.4377
	(0.9083)	(4.1918)	(3.4012)	(8.6402)	(0.5696)
PCGDP	0.0713**	0.1285	0.1186*	0.1368	-0.0003
	(0.0284)	(0.1119)	(0.0641)	(0.1698)	(0.0153)
PCGDP^2	-0.0017**	-0.0062*	-0.0014	-0.0040	0.0002
	(0.0008)	(0.0033)	(0.0013)	(0.0033)	(0.0004)
ISLAND	-0.1912	7.5209	1.4386	1.2780	0.4406
	(1.3509)	(5.3787)	(4.5774)	(11.3379)	(0.2715)
SL – General	0.8769***	0.7932***	0.7464***	0.5116***	0.2892***
	(0.0776)	(0.1113)	(0.1080)	(0.0710)	(0.0514)
SL – PES	-0.4392***	-0.2233***	-0.0384	-0.1396***	-0.0005
	(0.0478)	(0.0653)	(0.0253)	(0.0435)	(0.0044)
SL – POPD	1.1681	11.3951**	-1.3675	-22.5544**	-0.3960
	(1.3413)	(5.4235)	(4.4156)	(9.8489)	(0.7632)
SL – GCPOP	-0.8399	-3.3125	-3.4939	0.0334	0.2502
	(1.5624)	(6.1465)	(5.1637)	(12.3161)	(0.3089)
SL – PCGDP	-0.0245*	0.0235	-0.1146**	0.1259	-0.0008
	(0.0149)	(0.0546)	(0.0455)	(1.1154)	(0.0070)
N	173	173	173	163	117
R^2	0.8186	0.6962	0.4795	0.6133	0.3911

Model IV.9: Models with Specific Spatial Lags only: Shared Border Length Adjacency

Variable	Birds	Mammals	Reptiles	Amphibians	Vascular Plants
Constant	-3.8316***	-8.2071*	-8.2662**	20.8191**	0.4160
	(1.4345)	(4.9275)	(3.8191)	(8.8241)	(0.4570)
PES	0.3698***	0.2941***	0.0074	0.4942***	0.0099***
	(0.0223)	(0.0377)	(0.0187)	(0.0320)	(0.0023)
POPD	0.3976	-0.5120	0.0584	-1.0981	0.2879***
	(0.6404)	(0.6332)	(0.4908)	(1.1307)	(0.0603)
GCPOP	1.2080	9.1409**	5.8843	-14.2908	-0.5699
	(1.3779)	(4.4771)	(3.8963)	(9.4553)	(0.5512)
PCGDP	0.1191***	-0.1061	0.1210	0.1387	-0.0297**
	(0.0390)	(0.0937)	(0.1019)	(0.1856)	(0.0149)
$PCGDP^2$	-0.0031***	-0.0001	-0.0057*	-0.0056	0.0007*
	(0.0011)	(0.0020)	(0.0029)	(0.0036)	(0.0004)
ISLAND	3.3082*	11.4669*	8.5409*	-6.0863	0.4920*
	(1.8745)	(6.2083)	(5.1682)	(12.5245)	(0.2601)
SL – General	-	-	-	-	-
SL – PES	0.0759	-0.1363*	-0.0522*	0.0088	0.0049
	(0.0471)	(0.0784)	(0.0296)	(0.0395)	(0.0040)
SL – POPD	5.8887***	30.8456***	12.4403***	-10.5334	-0.9144
	(1.7846)	(5.7371)	(4.7172)	(10.6046)	(0.7201)
SL – GCPOP	4.7400**	8.2463	6.6923	-7.0749	0.5741*
	(2.0420)	(6.9535)	(5.7647)	(13.6369)	(0.2948)
SL – PCGDP	-0.0238	0.0081	-0.0327	0.0928	-0.0012
	(0.0208)	(0.0660)	(0.0508)	(0.1260)	(0.0065)
N	173	173	173	163	117
R^2	0.6592	0.5189	0.3090	0.5504	0.3291

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Figures in the parentheses are standard errors.

APPENDIX-V List of Sample Countries

Albania[1,2,3,4]

Algeria[1,2,3,4]

Angola[1,2,3,4]

Antigua and Barbuda[1,2,3,4]

Argentina[1,2,3,4]

Armenia[2,3]

Australia[1,2,3,4]

Austria[1,2,3,4]

Azerbaijan[1,2,3,4]

Bahamas[1,2,3,4]

Bahrain[2,3]

Bangladesh[2,3]

Barbados[1,2,3,4]

Belarus[2,3]

Belgium[1,2,3,4]

Belize[1,2,3,4]

Benin[2,3]

Bhutan[1,2,3,4]

Bolivia[1,2,3,4]

Bosnia and Herzegovina[2,3]

Botswana[1,2,3,4]

Brazil[2,3]

Brunei Darussalam[1,2,3,4]

Bulgaria[1,2,3,4]

Burkina Faso[2,3]

Burundi[2,3]

Cambodia[2,3]

Cameroon[1,2,3,4]

Canada[1,2,3,4]

Cape Verde[2,4]

Central African Republic[1,2,3,4]

Chad[2,3]

Chile[1,2,3,4]

China[1,2,3,4]

Colombia[1,2,3,4]

Comoros[2,4]

Congo[1,2,3,4]

Dominica[1,2,3,4]

Dominican Rep.[1,2,3,4]

Ecuador[1,2,3,4]

Egypt[1,2,3,4]

El Salvador[1,2,3,4]

Equatorial Guinea[1,2,3,4]

Eritrea[2,3]

Estonia[2,3]

Ethiopia[1,2,3,4]

Fiji[1,2,3,4]

Finland[2,3]

France[1,2,3,4]

Gabon[2,3]

Gambia[2,3]

Georgia[1,2,3,4]

Germany[1,2,3,4]

Ghana[1,2,3,4]

Greece[1,2,3,4]

Grenada[1,2,3,4]

Guatemala[1,2,3,4]

Guinea[1,2,3,4]

Guinea-Bissau[1,2,3,4]

Guyana[2,3]

Haiti[1,2,3,4]

Honduras[1,2,3,4]

Hungary[1,2,3,4]

Iceland[2,4]

India[1,2,3,4]

Indonesia[1,2,3,4]

Iran[2,3]

Ireland[2,3]

Israel[2,3]

Italy[1,2,3,4]

Jamaica[1,2,3,4]

Japan[1,2,3,4]

Jordan[2,3]

Kazakhstan[2,3]

Lebanon[2,3]

Lesotho[1,2,3,4]

Libya[1,2,3,4]

Lithuania[2,3]

Luxembourg[2,3]

Macedonia[2,3]

Madagascar[1,2,3,4]

Malawi[1,2,3,4]

Malaysia[1,2,3,4]

Maldives[2]

Mali[1,2,3,4]

Malta[1,2,3,4]

Mauritania[2,3]

Mauritius[1,2,3,4]

Mexico[1,2,3,4]

Moldova[2,3]

Mongolia[1,2,3,4]

Morocco[1,2,3,4]

Mozambique[1,2,3,4]

Myanmar[1,2,3,4]

Namibia[1,2,3,4]

Nepal[1,2,3,4]

Netherlands Antilles[2,3]

Netherlands[2,3]

New Zealand[1,2,3,4]

Nicaragua[1,2,3,4]

Niger[2,3]

Nigeria[1,2,3,4]

Norway[1,2,3,4]

Oman[1,2,3,4]

Pakistan[1,2,3,4]

Panama[1,2,3,4]

Papua New Guinea[2,3]

Paraguay[2,3]

Peru[1,2,3,4]

Philippines[1,2,3,4]

Poland[1,2,3,4]

Sao Tome&Principe[2,4]

Saudi Arabia[2,3]

Senegal[1,2,3,4]

Seychelles[1,2,3,4]

Sierra Leone[1,2,3,4]

Singapore[1,2,3,4]

Slovakia[1,2,3,4]

Slovenia[1,2,3,4]

Solomon Island[1,2,3,4]

South Africa[2,3]

South Korea[1,2,3,4]

Spain[1,2,3,4]

Sri Lanka[1,2,3,4]

St. Lucia[1,2,3,4]

Sudan[1,2,3,4]

Suriname[2,3]

Swaziland[1,2,3,4]

Sweden[1,2,3,4]

Switzerland[1,2,3,4]

Syria[2,3]

Taiwan[2,3]

Tajikistan[2,3]

Tanzania[1,2,3,4]

Thailand[2,3]

Togo[1,2,3,4]

Tonga[2,4]

Trinidad & Tobago[1,2,3,4]

Tunisia[2,3]

Turkey[1,2,3,4]

Turkmenistan[2,3]

Uganda[2,3]

Ukraine[2,3]

United Arab Emirates[2,3]

United Kingdom[1,2,3,4]

United States[1,2,3,4]

Uruguay[1,2,3,4]

Uzbekistan[1,2,3,4]

Costa Rica[1,2,3,4]	Kenya[1,2,3,4]	Portugal[1,2,3,4]	Vanuatu[2,4]
Côte d'Ivoire[1,2,3,4]	Kiribati[2,4]	Qatar[2]	Venezuela[1,2,3,4]
Croatia[2,3]	Kuwait[2]	Romania[1,2,3,4]	Viet Nam[1,2,3,4]
Cyprus[2,3]	Kyrgyzstan[2,3]	Russia[2,3]	Yemen[1,2,3,4]
Czech Republic[2,3]	Laos[2,3]	Rwanda[1,2,3,4]	Zambia[1,2,3,4]
Denmark[1,2,3,4]	Latvia[2,3]	Samoa[2,3]	Zimbabwe[1,2,3,4]
Djibouti[1,2,3,4]			

Note:

1 = Sample countries used in aggregate analysis
2 = Sample countries used in the analysis of birds, mammals, and reptiles
3 = Sample countries used in the analysis of amphibians
4 = Sample countries used in the analysis of vascular plants